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GREEN TILTS

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ABSTRACT

We estimate financial institutions' portfolio tilts related to stocks' environmental, social, and governance (ESG) characteristics. From 2012 to 2023, ESG related tilts consistently total about 6% of the investment industry's assets and rise from 17% to 27% of institutions' total portfolio tilts. Significant ESG tilts arise from the choice of stocks held and, especially, the weights on stocks held. The largest institutions tilt increasingly toward green stocks, while other institutions and households tilt increasingly brown. Divestment from brown stocks is typically partial rather than full, even for individual mutual funds. UNPRI signatories and European institutions tilt greener; banks tilt browner.

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1. Introduction

"Investing based on environmental, social, and governance (ESG) criteria has exploded in popularity, reaching $35 trillion in global assets under management (AUM) in 2020, according to Bloomberg Intelligence." Sentences like this introduce countless papers on ESG investing. Do such figures accurately reflect the amount of ESG investing? How closely do institutions' portfolio choices relate to companies' ESG characteristics? How have these ESG-related portfolio tilts evolved over time? Which investors tilt toward green assets, and which ones make the offsetting brown tilts? These are the questions we pursue. They are important because tilting green likely comes at a financial cost, given both theoretical arguments and empirical evidence that green assets have lower expected returns.[1]

As illustrated in our opening example, a common approach to measuring ESG investing is to sum the AUM of institutions that include ESG in their stated investment policies. While simple and transparent, this approach does not consider the extent to which such institutions actually modify their portfolios in ways related to assets' ESG characteristics. An institution may tilt its portfolio toward assets with favorable ESG characteristics, i.e., "green" assets, and away from unfavorable "brown" assets, but those tilts might be modest. The total AUM of such institutions surely overstates their ESG-related investing.

Another limitation of the usual approach works in the other direction: institutions not declaring an ESG policy could nevertheless be making portfolio decisions related to ESG characteristics. The reason is that such characteristics can enter not only for reasons related to social responsibility but also for financial reasons, which are less likely to appear in stated ESG policies. For example, an institution could overweight green stocks because it sees them as underpriced or as a hedge against climate risk.[2]

Our approach neither sums AUM nor screens by stated investment policies. Instead, we estimate ESG-related portions of investors' portfolio weights. We focus on U.S. stocks, and our primary analysis uses institutional holdings from 13F filings. For each institution, we estimate how stocks' ESG characteristics relate to their weights in the institution's portfolio, controlling for other stock attributes. Combining these estimates across stocks gives an institution-level ESG-related tilt. We aggregate those tilts across institutions to estimate the total ESG-related portfolio tilt in the investment industry.

We find that the total dollar ESG-related tilt consistently accounts for about 6% of the

[1] See Pástor, Stambaugh, and Taylor (2021, 2022) and Bolton and Kacperczyk (2021, 2023), among others.

[2] In their global survey of equity portfolio managers, Edmans, Gosling, and Jenter (2025) find that managers' primary motivation for using environmental and social criteria is to improve financial performance.

industry's equity AUM between years 2012 and 2023, reaching 6.5% by the end of the sample. By this measure, there is much less ESG investing than commonly reported. For example, 76% of our sample's AUM is managed by institutions that have signed the United Nations' Principles for Responsible Investment (UNPRI).

We analyze various dimensions of ESG-related tilts. For example, we consider both the extensive margin (i.e., which stocks are held) and the intensive margin (i.e., weights on stocks held). We find significant ESG tilts at both margins, though the intensive-margin tilts are two to three times larger. We also allow a stock's E, S, and G characteristics to relate separately to portfolio weights. This is a key virtue of our approach. One institution might care about G but not S, while another cares about S but not G. If a stock's E, S, and G characteristics are combined into a composite ESG score, the latter could rate two stocks equally, but one stock could be high G and low S while the other is low G and high S. The two institutions would tilt differently toward the two stocks, but those tilts would not be explained by the stocks' composite scores. When we restrict our estimation to the composite score, we find that over 40% of ESG-related tilts are missed.

We also assess ESG tilts in the context of institutions' overall portfolio tilts. For an institution less inclined to deviate from the market portfolio for any reason, a given ESG tilt is more economically significant, as it represents a greater disruption of what the institution would otherwise do, given its investing style or mandate. To measure total portfolio tilts—deviations of portfolio weights from market weights for any reason—we use the active share measure of Cremers and Petajisto (2009). On average, ESG tilts are about 20% as large as active share during our sample period. So, while ESG tilts are modest relative to AUM, they are more substantial relative to total tilts. Moreover, although ESG tilts have not grown as a share of AUM, they have grown as a share of total tilts: the average ratio of ESG tilt to active share has grown from 17% in 2012 to 27% in 2023.

We then examine whether ESG tilts are green or brown. Given the multiple dimensions of ESG, any of them can be used to measure greenness. For each dimension, we compute each institution's net tilt toward green stocks, or "GMB" tilt (green minus brown). From 2012 until a modest downturn in 2023, institutions become increasingly green, exhibiting a positive and rising aggregate GMB tilt. Offsetting that behavior, the aggregate portfolio of non-13F investors becomes browner, with a negative and decreasing GMB tilt. The rise in GMB tilts of 13F institutions occurs primarily via the intensive margin, that is, by increasingly overweighting green stocks and underweighting brown stocks. For example, divestment from brown stocks, a long-standing theme, occurs largely at the intensive margin, by reducing positions rather than eliminating them. All of these findings are robust across our four measures of greenness: E, S, G, and the composite score.

ESG investing varies greatly across 13F-filing institutions. For example, the rise in aggregate greenness is driven by the largest institutions. When we rank institutions by AUM and separate them at the 33rd and 66th percentiles, we find that only the top third exhibits a positive and rising GMB tilt. In contrast, the GMB tilts of the middle and bottom thirds of institutions are mostly negative and decreasing over time—meaning brown and becoming browner. For the biggest institution, BlackRock, the GMB tilt becomes especially large through 2020 but declines thereafter.

As noted earlier, we do not rely on institutions' stated ESG policies to estimate ESG tilts. We do ask, however, whether those policies relate to our estimated tilts, specifically, whether institutions that have signed the UNPRI have larger GMB tilts. We find that UNPRI signatories are significantly greener. This result holds across institutions and, based on environmental greenness, also over time: institutions tend to become greener after signing the UNPRI. We also find that banks are browner than other institutions, especially insurance companies, and that European institutions are greener (i.e., European institutions' holdings of U.S. equities are greener than U.S. institutions' holdings of those equities).

We construct firms' ESG characteristics using ESG ratings from MSCI, a leading data provider. For robustness, we re-estimate institutional tilts using ratings from Sustainalytics. The results are very similar; for example, the aggregate ESG-related tilt ranges from 5.9% to 6.7% of AUM, and our main conclusions remain unchanged.

Results are also similar when using industry-adjusted ESG scores, computed by subtracting industry averages from firms' scores. The resulting ESG tilts are smaller, averaging 4% to 5%, but otherwise behave similarly to the unadjusted tilts. The same holds for industry-adjusted green and brown tilts. Again, our conclusions remain unchanged.

ESG tilts reflect decisions having diverse origins, such as different managerial layers within an institution. In a mutual fund family, for example, an active fund's tilt is chosen by the fund's portfolio manager, while a passive fund inherits the tilt of the index it tracks, chosen by fund-family management. In other cases, ESG tilts reflect decisions made outside the institution. For example, client mandates could dictate ESG tilts (or the absence thereof) in the portfolios of bank-administered trusts or advisor-managed separate accounts. We adopt an inclusive approach, not confining our analysis to tilts traceable to particular decision origins. Moreover, we focus on AUM-weighted tilts, which ultimately reflect the decisions of asset owners, who decide where the AUM resides.

Computing an institution's ESG tilt from 13F holdings may obscure offsetting tilts across separate investing entities within the institution. For example, a mutual fund family with half its AUM in green-tilting funds and half in brown-tilting funds may show little ESG tilt in its 13F holdings. In that sense, our estimates likely understate the tilts we would see if we could disaggregate the entities within each institution. Even for institutions that available data allow us to disaggregate, namely mutual fund families, the data limit the disaggregation. For example, mutual funds often employ multiple managers or sub-advisors managing separate "sleeves" that aggregate to the observed fund portfolio. It seems hard, even in theory, to identify a uniquely meaningful level of disaggregation, let alone one with empirical relevance. Quite simply, institutions' 13F holdings offer a consistent and feasible level of aggregation for analyzing ESG tilts across the investment industry.

To complement this institution-level analysis, we estimate ESG tilts for U.S. equity mutual funds, using fund-level holdings from the S12 dataset. Disaggregating the holdings of mutual fund families allows us to uncover ESG tilts that offset within families. We find these offsets to be modest: in 2023, they account for 1.8% of fund families' AUM, or just under 0.5% of aggregate AUM—one fourteenth of the total ESG tilt.

Mutual funds' total ESG tilt ranges from 6% to 10% of AUM, and from 10% to 13% for actively managed funds. Extensive-margin tilts are about twice as large as those for institutions but remain below intensive-margin tilts. Similarly, extensive-margin divestment from brown stocks exceeds that of institutions but still falls short of intensive-margin divestment, indicating that for individual mutual funds, just like for 13F institutions, brown divestment is more partial than full. Mutual funds collectively tilt green, though not as much as all institutions in aggregate. ESG-labeled funds exhibit larger green tilts and smaller brown tilts than their non-ESG counterparts.

ESG investing is distinct from index investing, i.e., holding the market portfolio. While investors' ESG preferences can affect market weights, we do not view pure index investors as engaging in ESG investing. Our framework assigns zero ESG tilts to index investors, as we control for market weights when estimating tilts. We also show that over the past decade, the market portfolio itself has increasingly tilted toward environmentally green stocks.

Our paper contributes to the large literature that studies the composition of institutional portfolios. This literature documents various institutional investors' preference for large and liquid stocks (e.g., Falkenstein (1996), Gompers and Metrick (2001), Bennett et al. (2003), and Ferreira and Matos (2008)). Institutions' portfolio holdings are also related to stock characteristics such as the book-to-market ratio, prior-year return, and various risk measures.[3] We estimate institutions' ESG-related portfolio tilts while controlling for non-ESG stock characteristics that prior work relates to portfolio weights.

We are not the first to examine institutions' portfolio tilts with respect to stocks' ESG characteristics. For example, Ferreira and Matos (2008) document institutions' preference for firms with good governance. Bolton and Kacperczyk (2021) find that institutions underweight firms with high scope-1 carbon emission intensity. Atta-Darkua et al. (2022) find that institutions that join climate-related investor initiatives increase their holdings of firms with low carbon emissions. Starks, Venkat, and Zhu (2023) find that institutions with longer investment horizons tilt their portfolios more towards firms with high ESG scores. Gibson, Krueger, and Mitali (2021) relate institutions' portfolio-level environmental and social scores to performance. Nofsinger, Sulaeman, and Varma (2019) find that institutions underweight stocks with negative environmental and social indicators. Hong and Kostovetsky (2012) find that Democratic-leaning fund managers allocate less to the stocks of firms viewed as socially irresponsible. Choi, Gao, and Jiang (2020a) show that institutions reduced the carbon exposures of their portfolios between 2001 and 2015. Starks (2023) shows that U.S. active mutual funds have increased their ownership of high-ESG firms between 2013 and 2021.

Like some of these studies, we find that institutions' portfolios tilt green, and increasingly so. However, our approach to measuring ESG-related portfolio tilts is fundamentally different. We do not analyze portfolio-level ESG characteristics because they reflect also stocks' non-ESG characteristics such as size and book-to-market, which are correlated with ESG characteristics. By controlling for non-ESG characteristics, our approach separates ESG tilts from investment styles such as large-cap growth. Our approach has two additional advantages. First, it measures the extensive- and intensive-margin components of ESG tilts, yielding new insights, such as that divestment from brown stocks occurs largely at the intensive margin. Second, instead of analyzing one ESG characteristic at a time, our approach uses all three characteristics simultaneously. Moreover, these characteristics enter separately, capturing the fact that different institutions care about different dimensions of ESG.

In a complementary study, Cremers, Riley, and Zambrana (2023) develop a new measure of how actively a fund uses ESG information. Their measure, which they call active ESG share, is very different from ours: it compares the distribution of a portfolio's stock-level ESG scores to that of its benchmark. Their focus is also different in that they relate their measure to fund performance. They do not examine aggregate tilts, nor do they compare

[3]See, for example, Falkenstein (1996), Gompers and Metrick (2001), Edelen, Ince, and Kadlec (2016), DeVault, Sias, and Starks (2019), Koijen and Yogo (2019), and Lettau, Ludvigson, and Manoel (2021). Lewellen (2011) shows that institutions' aggregate holdings closely resemble those of the market portfolio.

green vs. brown tilts or intensive vs. extensive margins.

Existing studies find mixed evidence on whether UNPRI signatories engage in ESG-related behavior, raising concerns about greenwashing (Gibson et al. (2022), Humphrey and Li (2021), Kim and Yoon (2023), and Liang, Sun, and Teo (2022)). We find that UNPRI signatories' portfolios tend to exhibit greener tilts.

Prior evidence on ESG-related trading by retail investors is also mixed. On the one hand, Choi, Gao, and Jiang (2020b) find that retail investors, but not institutions, respond to abnormally warm temperatures by selling stocks of carbon-intensive firms. Li, Watts, and Zhu (2023) find that retail investors' trades respond to a broader set of ESG news events. On the other hand, Moss, Naughton, and Wang (2021) find that retail investors' buy and sell decisions do not respond to ESG disclosures. Instead of analyzing responses to news or disclosures, we focus on ESG-related portfolio tilts. We find that the portfolios of non-13F investors, most of whom are retail investors, tilt brown, and increasingly so.

Our study also relates to the literature exploring links between ownership by institutions, including responsible ones, and various aspects of corporate social responsibility.[4] Our focus on institutions' ESG tilts provides a different and complementary perspective on institutional responsibility. Finally, our study relates to those that estimate ESG-related asset demands in other ways, to address different issues, such as price impact.[5]

The remainder of the paper is organized as follows. Section 2 defines ESG-related tilts. Section 3 outlines our estimation procedure. Section 4 presents evidence on ESG tilts for a large sample of institutional investors. Section 5 examines mutual funds' tilts. Section 6 analyzes the greening of the market portfolio. Section 7 concludes.

2. ESG-related tilts

To quantify the amount of ESG investing, we measure the extent to which investors tilt their portfolios in relation to stocks' ESG characteristics. We denote the set of all stocks' ESG characteristics by $\mathcal{G}$. Each stock has multiple ESG characteristics. We denote neutral values of the same characteristics by $\mathcal{G}_0$. Specifically, $\mathcal{G}_0$ is the counterpart of $\mathcal{G}$ in which each stock's value of each ESG characteristic is replaced by the market portfolio's value of

[4] See, for example, Chen, Dong, and Lin (2020), Choi et al. (2023), Dyck et al. (2019), Gantchev, Giannetti, and Li (2022), Heath et al. (2021), Hwang, Titman, and Wang (2022), Ilhan et al. (2020), and Li and Raghunandan (2021).

[5] See Koijen, Richmond, and Yogo (2022), Noh, Oh, and Song (2023), and van der Beck (2022).

the same characteristic. Let w_{in} denote investor i's portfolio weight on stock n. For any given investor-stock pair, we define the investor's ESG-related portfolio tilt in this stock as

$$\Delta_{in} = \mathrm{E}[w_{in}|\mathcal{G}, \mathcal{C}] - \mathrm{E}[w_{in}|\mathcal{G}_0, \mathcal{C}]\,, \tag{1}$$

where E denotes a conditional expectation and $\mathcal{C}$ is the set of stocks' non-ESG stock characteristics. Δ_{in} is the part of w_{in} attributable to the difference between $\mathcal{G}$ and $\mathcal{G}_0$, holding constant the non-ESG characteristics. Holding $\mathcal{C}$ constant is important because the ESG and non-ESG characteristics can be correlated. For example, Pástor, Stambaugh, and Taylor (2022) show that stocks with lower book-to-market ratios tend to have higher environmental ratings (i.e., growth stocks tend to be greener than value stocks). By including a stock's book-to-market ratio among the non-ESG characteristics, we control for this ratio in estimating the relation between $\mathcal{G}$ and portfolio weights. We conduct our analysis at a given point in time, t, but we suppress the variables' dependence on t, for simplicity.

The above definition of Δ_{in}, a difference in conditional expectations, has a familiar analogue in regression analysis. A common way to quantify an independent variable's contribution to the dependent variable is to compare fitted values (estimated conditional expectations) for two values of the independent variable, such as the latter's actual value and its sample average. One could, for example, follow that procedure and estimate Δ_{in} by just regressing, across stocks, w_{in} on stock n's ESG and non-ESG characteristics. We avoid that simple regression approach for two reasons. First, how an investor weights a stock depends on its attractiveness relative to other stocks in the investor's portfolio, and that comparison involves the other stocks' characteristics as well. Second, we include portfolio choices made at the extensive margin, not just the intensive, as there are often many stocks for which $w_{in} = 0$. That feature of the data is poorly suited for the simple regression.

2.1. Extensive- and intensive-margin tilts

The conditional expectations entering the value of Δ_{in} in equation (1) can be written as $\mathrm{E}[w_{in}|\cdot] = \mathrm{Prob}\{w_{in} > 0|\cdot\} \times \mathrm{E}[w_{in}|w_{in} > 0, \cdot]$, under the assumption that $w_{in} \geq 0$.[6] Therefore, $\mathcal{G}$ relates to w_{in} through two channels: the probability that investor i holds stock n and the amount invested in the stock if held. To quantify both channels, for any set of ESG characteristics $\tilde{\mathcal{G}}$, we denote

$$\pi(\tilde{\mathcal{G}}) \equiv \mathrm{Prob}\{w_{in} > 0|\tilde{\mathcal{G}}, \mathcal{C}\} \tag{2}$$

$$w^+(\tilde{\mathcal{G}}) \equiv \mathrm{E}[w_{in}|w_{in} > 0; \tilde{\mathcal{G}}, \mathcal{C}]\,. \tag{3}$$

[6]This assumption accommodates our data. Reported holdings of institutions and funds include only long stock positions. For stocks that are not held long, we set $w_{in} = 0$ in our empirical implementation.

We apply these formulas for two different values of $\tilde{\mathcal{G}}$: the observed values, $\mathcal{G}$, and the neutral values, $\mathcal{G}_0$. We can thus rewrite equation (1) as $\Delta_{in} = \pi(\mathcal{G})w^+(\mathcal{G}) - \pi(\mathcal{G}_0)w^+(\mathcal{G}_0)$. We can then split Δ_{in} into two components,

$$\Delta_{in} \quad = \quad \Delta_{in}^{ext} + \Delta_{in}^{int}\,, \tag{4}$$

representing the extensive- and intensive-margin tilts, respectively. These components are

$$\Delta_{in}^{ext} \quad = \quad w^+(\mathcal{G}_0)\left\{\pi(\mathcal{G}) - \pi(\mathcal{G}_0)\right\} \tag{5}$$

$$\Delta_{in}^{int} \quad = \quad \pi(\mathcal{G})\left\{w^+(\mathcal{G}) - w^+(\mathcal{G}_0)\right\}. \tag{6}$$

The extensive-margin tilt, Δ_{in}^{ext}, is computed by varying the probability of holding the stock, without changing the expected portfolio weight conditional on holding the stock. This tilt answers the question: how much of investor i's weight in stock n is attributable to the relation between the stock's ESG characteristics and the probability of holding the stock?

The intensive-margin tilt, Δ_{in}^{int}, is computed by varying the expected portfolio weight conditional on holding the stock, without changing the probability of holding the stock. This tilt answers the question: how much of investor i's weight in stock n relates to the stock's ESG characteristics, conditional on holding the stock?

2.2. Investor-level tilts

We compute investor i's ESG-related portfolio tilt by adding up the absolute values of the investor's portfolio tilts with respect to each of the N stocks:

$$T_i = \frac{1}{2}\sum_{n=1}^{N} |\Delta_{in}|\,. \tag{7}$$

This definition parallels that of the ESG tilt in Pástor, Stambaugh, and Taylor (2021), except that here Δ_{in} is not simply a deviation of the stock's portfolio weight from its market weight. The division by two ensures that we avoid double-counting: for each stock the investor overweights because of $\mathcal{G}$, the investor must underweight one or more other stocks. Put differently, $\sum_{n=1}^{N}\Delta_{in} = 0$ for all i, which follows from equation (1), so any positive Δ_{in}'s must be balanced by negative ones.

We similarly compute the investor's intensive- and extensive-margin tilts:

$$T_i^{int} = \frac{1}{2}\sum_{n=1}^{N} |\Delta_{in}^{int}| \tag{8}$$

$$T_i^{ext} = \frac{1}{2}\sum_{n=1}^{N} |\Delta_{in}^{ext}| \,. \tag{9}$$

Note that, in general, $T_i \neq T_i^{int} + T_i^{ext}$. While Δ_{in} can be decomposed cleanly into Δ_{in}^{int} and Δ_{in}^{ext} (see equation (4)), decomposing $|\Delta_{in}|$ is less straightforward. In particular, $|\Delta_{in}| = |\Delta_{in}^{int} + \Delta_{in}^{ext}| \leq |\Delta_{in}^{int}| + |\Delta_{in}^{ext}|$, and the inequality is strict if and only if Δ_{in}^{int} and Δ_{in}^{ext} have opposite signs. It follows immediately that $T_i \leq T_i^{int} + T_i^{ext}$.

2.3. Aggregate tilts

Let A_i denote the dollar value of investor i's assets. For any given set of investors, $\mathcal{S}$, we can compute the aggregate tilt as an asset-weighted average tilt across investors:

$$T = \frac{1}{A}\sum_{i\in\mathcal{S}} A_i T_i \,, \tag{10}$$

where $A = \sum_{i\in\mathcal{S}} A_i$. T measures the fraction of total investor assets that is "tilted."

We compute aggregate intensive- and extensive-margin tilts analogously:

$$T^{int} = \frac{1}{A}\sum_{i\in\mathcal{S}} A_i T_i^{int} \tag{11}$$

$$T^{ext} = \frac{1}{A}\sum_{i\in\mathcal{S}} A_i T_i^{ext} \,. \tag{12}$$

2.4. Green and brown tilts

The tilt measures presented so far capture all ESG-related portfolio tilts, regardless of their direction. Two investors with identical T_i values could in principle be using ESG characteristics in opposite ways, one tilting toward and the other away from stocks with high values of these characteristics. Next, we design directional tilt measures that separate "green" investment behavior from "brown." Green behavior tilts toward green stocks and away from brown stocks, whereas brown behavior tilts in the opposite direction.

To define directional tilt measures, we must designate stocks as green or brown. That is not straightforward with multiple ESG characteristics, as stocks with high values of one characteristic could have low values of another. For any given ESG characteristic, however, such as a composite ESG rating or an E score, we can define greenness in terms of that characteristic. Let g_n denote stock n's value of that characteristic and g_0 the characteristic's neutral value—the capitalization-weighted average of g_n across stocks. We classify the stock as green if $g_n \geq g_0$ and brown if $g_n < g_0$. In other words, a stock is green if it is greener than the market portfolio and brown if it is browner than the market portfolio.

For each $\{i, n\}$ pair, we classify the tilt into one of four categories. Consequently, each Δ_{in} from equation (1) takes one of the following four values (the other three are zero):

$$\Delta_{in}^{OG}: \quad \text{when } \Delta_{in} > 0 \text{ and } g_n \geq g_0: \quad \text{Overweight Green stocks} \quad \text{(green tilt)} \tag{13}$$
$$\Delta_{in}^{UB}: \quad \text{when } \Delta_{in} < 0 \text{ and } g_n < g_0: \quad \text{Underweight Brown stocks} \quad \text{(green tilt)} \tag{14}$$
$$\Delta_{in}^{OB}: \quad \text{when } \Delta_{in} > 0 \text{ and } g_n < g_0: \quad \text{Overweight Brown stocks} \quad \text{(brown tilt)} \tag{15}$$
$$\Delta_{in}^{UG}: \quad \text{when } \Delta_{in} < 0 \text{ and } g_n \geq g_0: \quad \text{Underweight Green stocks} \quad \text{(brown tilt)}\,. \tag{16}$$

There are two types of "green tilts," which reflect green investment behavior, and two types of "brown tilts," which reflect brown investment behavior. An investor can tilt green by either overweighting green stocks or underweighting brown stocks. An investor can tilt brown by either overweighting brown stocks or underweighting green stocks.

Aggregating the signed tilts across stocks to the investor level, we define

$$T_i^{OG} = \sum_{n=1}^{N} \Delta_{in}^{OG}\,, \qquad T_i^{UB} = -\sum_{n=1}^{N} \Delta_{in}^{UB}\,, \qquad T_i^{OB} = \sum_{n=1}^{N} \Delta_{in}^{OB}\,, \qquad T_i^{UG} = -\sum_{n=1}^{N} \Delta_{in}^{UG}\,. \tag{17}$$

We put minus signs in front of two of the sums to ensure that all four tilts are nonnegative. For a given investor i, all four tilts can be strictly positive—the investor can be overweighting some green stocks while underweighting others, and similarly for brown stocks.

To quantify a given investor's overall green and brown behaviors, we combine the above tilts to measure the investor's total green tilt (T_i^G) and total brown tilt (T_i^B):

$$T_i^G = T_i^{OG} + T_i^{UB} \geq 0 \tag{18}$$
$$T_i^B = T_i^{OB} + T_i^{UG} \geq 0\,. \tag{19}$$

We also compute the investor's green-minus-brown tilt as[7]

$$T_i^{GMB} = T_i^G - T_i^B\,. \tag{20}$$

[7] An alternative way to compute this quantity is $T_i^{GMB} = \sum_{n \in \mathcal{S}_G} \Delta_{in} - \sum_{n \in \mathcal{S}_B} \Delta_{in}$, where $\mathcal{S}_G$ and $\mathcal{S}_B$ denote the sets of all green and brown stocks, respectively.

$T_i^{GMB} > 0$ indicates that the investor's behavior is green overall, whereas $T_i^{GMB} < 0$ indicates net brown behavior. For comparison, note that the unsigned tilt from equation (7) equals

$$
\begin{aligned}
T_i &= \frac{1}{2}(T_i^{OG} + T_i^{UB} + T_i^{OB} + T_i^{UG}) && (21)\\
&= \frac{1}{2}(T_i^{G} + T_i^{B})\,. && (22)
\end{aligned}
$$

The value of T_i thus represents the average of the green and brown tilts T_i^G and T_i^B, whereas T_i^{GMB} represents their difference.

We also compute asset-weighted averages across investors, analogous to equations (10) through (12), yielding the aggregate tilt measures T^G, T^B, and T^{GMB}. If the aggregates are computed across all investors, the green and brown tilts are always equal:

$$T^G = T^B\,, \tag{23}$$

as we prove in the Appendix. Given that the green and brown tilts fully offset each other, the value of T^{GMB} computed across all investors is zero. Nonetheless, T^{GMB} can be nonzero when computed across subsets of investors, as we show later.

Finally, we separate the green and brown tilts into their extensive- and intensive-margin components. We first split the Δ_{in}'s in equations (13) through (16) into two parts, as in equation (4). We then aggregate those parts to the investor level, as in equations (8) and (9), and then to the aggregate level, as in equations (10) through (12).

3. Estimation framework

To estimate the portfolio tilts from Section 2, we first estimate two quantities: π_{in}, the probability of investor i holding stock n, and w_{in}^+, the expected weight conditional on holding the stock (see equations (2) and (3)). With those estimates in hand, we compute the components of Δ_{in} in equations (5) and (6), which yield Δ_{in} in equation (4).[8] We then aggregate the Δ_{in} estimates into the tilts defined in Section 2. We estimate π_{in} and w_{in}^+ separately for each quarter t, but we continue suppressing the t subscripts, as in Section 2.

Estimating π and w^+ requires a model for portfolio weights. In Section 3.1, we describe our econometric model for the extensive margin of portfolio weights, which yields an estimate of π. In Section 3.2, we present our model for the intensive margin, which yields an estimate

[8] Note that Δ_{in} is defined for all stocks n, including stocks not actually held by investor i.

of w^+, after incorporating a selection correction described in Section 3.3. In Section 3.4, we discuss how we adjust our estimates for potential bias and compute their standard errors.

We arrange the elements of $\mathcal{G}$ into an $N \times K_1$ matrix G of the N stocks' ESG characteristics. We also arrange the elements of $\mathcal{C}$ into an $N \times K_2$ matrix C of non-ESG characteristics, which include stocks' market capitalization weights. We define $X \equiv [\iota \; G \; C]$, where ι is an N-vector of ones, so that X is an $N \times K$ matrix, where $K = 1 + K_1 + K_2$. Let x_{nj} denote the (n, j) element of X, and X_n its nth row. We ensure that all elements of X are non-negative (by using cross-sectional percentiles of raw characteristics, as we explain later).

We estimate tilts related to ESG characteristics, but our methodology can be used to estimate tilts related to other characteristics of interest. That is, let $\mathcal{G}$ contain those characteristics and $\mathcal{C}$ contain other characteristics included as controls. The tilts defined in Section 2 are then reinterpreted as tilts related to the characteristics in $\mathcal{G}$. A key aspect of our methodology in general is that it estimates tilts at the extensive margin in addition to the intensive margin. An alternative approach for analyzing just the latter is Koijen and Yogo (2019), who take as exogenous the stocks an institution weights positively and then estimate a model determining those weights.

3.1. Extensive margin

Our model of the extensive margin gives the value of

$$\pi_{in} \equiv \text{Prob}\{w_{in} > 0 | X\} \,. \tag{24}$$

We assume that π_{in} for each investor-stock pair is given by an investor-specific probit model:

$$\pi_{in} = \Phi(X_n a_i) \,, \tag{25}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution.

We estimate the model in equation (25) for each investor i across all stocks with non-missing data; as a result, the number of observations is the same for all investors. The dependent variable is an indicator $1_{w_{in}>0}$, which is equal to one if stock n is held by investor i and zero otherwise. We estimate the coefficients a_i by maximum likelihood and denote the fitted value by $\hat{\pi}_{in}$. The estimated probabilities $\hat{\pi}_{in}$ lie between 0 and 1, by construction. Additional details, including on goodness of fit, are in the Online Appendix.

Suppose X were to include all of the information used by investor i, such that $1_{w_{in}>0}$ depends deterministically on X. The latter dependence could involve all rows of X, not just

X_n, but that dependence would likely be complicated, having no analytic solution, especially with realistic constraints on asset weights faced by many institutions.[9] Given that any X we specify empirically is only a subset of the investor's information, the dependence of $1_{w_{in}>0}$ on X is probabilistic, not deterministic. We condition the probability in equation (25) on just X_n for parsimony and tractability. The modeled randomness in $1_{w_{in}>0}$ therefore reflects the omission of information as well as uncertainty about how information determines the institution's asset choices. We construct X_n as the cross-sectional percentiles of asset n's characteristics, as explained later, so to that extent X_n incorporates cross-asset information. All stocks' X_n values affect the probit estimate of a_i, which is another way cross-asset information enters.

3.2. Intensive margin

Our model of the intensive margin gives the value of

$$w_{in}^{+} \equiv \mathrm{E}[w_{in}|w_{in} > 0, X, \pi_i]\,. \tag{26}$$

The expectation in equation (26) conditions on the full set of probabilities $\pi_i \equiv [\pi_{i1} \cdots \pi_{iN}]'$ and the full matrix X, because an investor's expected weight on a given stock can depend on what other stocks, and characteristics thereof, the investor could hold as well. For example, the portfolio weight on each stock held by the investor can depend on the greenness of all stocks, including stocks not held.

We model w_{in}^{+} as a restricted linear function of stock n's characteristics, after scaling it by the stock's market portfolio weight, w_{mn}. Specifically, we assume that

$$\frac{w_{in}^{+}}{w_{mn}} = \sum_{j=1}^{K} c_{ij} x_{nj}\,, \quad n = 1, \ldots, N, \tag{27}$$

so that w_{in}^{+} is linear in the K values of $w_{mn}x_{nj}$. If stock n is held, its expected weight could in principle depend not only on the stock's own value of $w_{mn}x_{nj}$ but also on the values of that quantity for other stocks the investor may hold. Recognizing that potential dependence, we allow c_{ij} to depend on the portfolio's expected sum of $w_{mn}x_{nj}$ across stocks. We also restrict the expected portfolio weights to add up to one:

$$\sum_{n=1}^{N} \pi_{in} w_{in}^{+} = 1\,, \tag{28}$$

[9] For example, even a standard mean-variance optimization with short-sale constraints generally does not admit an analytic solution.

as long as π_i has at least one positive element. As we show in the Appendix, we can then estimate w^+_{in}/w_{mn} by the fitted values from the regression

$$\frac{w_{in}}{w_{mn}} = \sum_{j=1}^{K} b_{ij}\tilde{x}_{inj} + e_{in}\,, \quad n = 1, \ldots, N, \tag{29}$$

where $\sum_{j=1}^{K} b_{ij} = 1$ and the j-th independent variable is

$$\tilde{x}_{inj} = \frac{x_{nj}}{\sum_{n=1}^{N} \pi_{in} w_{mn} x_{nj}}\,. \tag{30}$$

This regression's error term, e_{in}, could in principle be heteroskedastic, but this concern should be alleviated by our use of scaled portfolio weights, w_{in}/w_{mn}, on the left-hand side. In fact, the main reason why we scale w_{in} by the market weight in equation (27) is to reduce the heteroskedasticity in e_{in}. If we worked with raw weights w_{in} instead, e_{in}'s would likely be more volatile for larger firms (whose portfolio weights tend to be larger).

To derive the regression model in equation (29), we assume that for each stock n,

$$w_{in} = w^+_{in} + \epsilon_{in}\,, \tag{31}$$

with $\mathrm{E}[\epsilon_{in}|X] = 0$. The assumption that $\mathrm{E}[\epsilon_{in}|X] = 0$ merits discussion in light of alternative treatments such as Koijen and Yogo (2019). Following their argument, note that ϵ_{in} includes effects on w_{in} of the stock's characteristics that our model omits. Let ζ_n denote such a characteristic. If ζ_n is related to demands for stock n by a substantial mass of investors, then ζ_n can affect the stock's price, p_n, making ϵ_{in} correlated with p_n. Because X includes variables that contain p_n, such as the market weight w_{mn}, the assumption $\mathrm{E}[\epsilon_{in}|X] = 0$ then fails.

While the above scenario of non-zero correlation between ϵ_{in} and p_n is possible, it does not even imply a sign for the correlation. In particular, let $\bar{\lambda}\zeta_n$ denote the effect of ζ_n on p_n, and let the contribution of ζ_n to w_{in} be $\lambda_i\zeta_n$. The correlation between ϵ_{in} and p_n is positive (negative) if λ_i and $\bar{\lambda}$ have the same (opposite) sign. Suppose the investor is an actively managed fund. (For a passive fund, we are presumably not omitting a relevant ζ_n.) Suppose ζ_n reflects positive noise-trader sentiment injecting a positive component, $\bar{\lambda}\zeta_n$, into the equilibrium p_n. On one hand, an active manager with sufficient skill to recognize that effect underweights the stock, giving the fund's λ_i the opposite sign of $\bar{\lambda}$. That opposite sign occurs even if the fund and others with similar skill exert negative pressure on p_n in the process of underweighting the stock. The decision to underweight the stock is made with full knowledge of the accompanying p_n, whatever the forces determining that equilibrium price. On the other hand, an active manager with less skill can be infected with the same positive sentiment as the noise traders, giving that fund's λ_i the same sign as $\bar{\lambda}$. Because even the sign of any correlation between ϵ_{in} and p_n is ambiguous, we adopt $\mathrm{E}[\epsilon_{in}|X] = 0$ as a reasonable simplification. Also motivating this simplification is that we do not focus on the relation between w_{in} and the price-related variables in X.

3.3 Selection correction

The regression in equation (29) assumes that for each stock n in the N-stock universe, if investor i were to hold the stock, the weight they would place on it, w_{in}, would obey that equation, with $\mathrm{E}[e_{in}|X] = 0$. The values of w_{in} we use in estimating the regression in equation (29) can be only those for the subset of stocks actually held by the investor. If the probability of holding stock n is correlated with e_{in}, then e_{in} need not have zero expectation conditional on stock n being in that selected subset. Estimates of b_{ij} can be inconsistent if this selection effect is not corrected.

To correct for selection, we follow the two-step procedure of Heckman (1979), as described in the Appendix. We find empirically that the selection correction matters more for institutions holding fewer stocks, for which selection is more likely to matter. Given that institutions holding fewer stocks tend to be smaller, the correction makes relatively little difference in the aggregate asset-weighted tilt estimates (see the Online Appendix).

3.4 Bias adjustment and standard errors

The coefficients in equations (25) and (29) are consistently estimated, and thus so are the values of Δ_{in} and the resulting tilts defined in Section 2. The finite-sample properties of those estimates are not evident, however. We therefore conduct bootstrap simulations to adjust for any potential biases in our estimated tilts and to obtain standard errors.

For example, to de-bias the raw estimates of T_i, which we denote by T_i^{raw}, we simulate many samples of portfolio weights, which we denote by $\tilde{w}_{in}$, by resampling the residuals from the extensive- and intensive-margin regressions estimated on the sample of observed weights, w_{in}. For each simulated sample $\tilde{w}_{in}$, we estimate the extensive- and intensive-margin regressions on that sample, obtaining an estimate of the investor-level tilt, which we denote by $\tilde{T}_i$. We estimate the bias in T_i^{raw} as $TBias_i = \bar{\tilde{T}}_i - T_i^{raw}$, where $\bar{\tilde{T}}_i$ is the average value of $\tilde{T}_i$ across simulations. Our bias-adjusted estimate of T_i is $T_i^{raw} - TBias_i$. The details of the bootstrap procedure are in the Appendix.

An important by-product of this procedure is the standard error of T_i, which we obtain from the standard deviation of the $\tilde{T}_i$'s across simulations. Again, the details are in the Appendix. All of the standard errors reported in the paper are bootstrapped.

4. Estimates of ESG tilts: Financial institutions

This section presents our main empirical findings. Using the econometric framework from Section 3, we estimate the ESG-related portfolio tilts introduced in Section 2 for a comprehensive sample of institutional investors. After describing our data in Section 4.1, we analyze total ESG tilts in Section 4.2, followed by green and brown tilts in Section 4.3. In Section 4.4, we examine how the tilts vary across institutions. In Section 4.5, we study tilts based on industry-adjusted ESG scores. Finally, in Section 4.6, we assess the robustness of our results using ESG metrics from an alternative data provider.

4.1. Data

We estimate the model using quarterly panel data on institutional investment managers that file Form 13F with the Securities and Exchange Commission. An institution is required to file this form if its holdings of U.S. stocks exceed \$100 million. Here, "institution" refers to an investment company such as Fidelity, not its individual funds. Most sample institutions are investment advisors, but the sample also includes banks, insurance companies, pension funds, and endowments. It also includes non-U.S. institutions' holdings of U.S. stocks.

We obtain the 13F holdings data from Thomson/Refinitiv. From these data, we compute institutions' quarterly portfolio weights w_{in} among the subset of "covered" stocks, meaning stocks with non-missing ESG and non-ESG characteristics. There are roughly 2,000 covered stocks throughout our sample period. In 2023, covered stocks account for 86% of the combined market capitalization of all CRSP stocks.[10] We define an institution's AUM to be its combined dollar holdings of covered stocks.

We exclude institutions with less than \$100 million in total 13F holdings (covered and uncovered), less than 50% of their total 13F dollar holdings in covered stocks, and, to allow sufficient precision in the intensive model, fewer than 30 covered stocks held. These filters drop institutions that together account for just 3.8% of covered stocks' total market capitalization in 2023.

[10]We study stocks with CRSP share codes of 10, 11, 12, or 18.

The number of institutions in our sample ranges from 1,727 in 2012 to 3,260 in 2023. Institutions' combined AUM increases from \$9.7 trillion to \$31.5 trillion during that period. The institutions hold between 63% and 70% of covered stocks' combined market capitalization during our sample period.

Our measures of ESG characteristics follow Pástor, Stambaugh, and Taylor (2022), who use data from MSCI, the world's largest provider of ESG ratings (e.g., Eccles and Stroehle, 2018, and Berg et al., 2023). Berg, Heeb, and Koelbel (2023) find that among the ESG ratings from five major providers, MSCI's rating is the most important in explaining ESG fund holdings. They also note that MSCI has the largest market share in the ESG data market. The MSCI data cover more companies than other ESG raters (Berg et al., 2022) and provide granular industry-unadjusted measures. Our sample begins in 2012q4, when MSCI greatly expanded its coverage.

We compute environmental greenness as in Pástor, Stambaugh, and Taylor (2022), interacting the MSCI variables "Environmental Pillar Score" and "Environmental Pillar Weight."[11] We compute social and governance greenness the same way, replacing MSCI's E variables with their S and G counterparts. In most of our analysis, each stock's ESG characteristics are represented by a 3×1 vector representing E, S, and G greenness. In some of our analysis, there is only one ESG characteristic per stock: the stock's composite ESG score, which is equal to MSCI's Weighted Average Key Issue score. This composite score equals the sum of our E, S, and G greenness measures plus a constant.

In the set of non-ESG stock characteristics, we include seven variables that are commonly used in portfolio construction: market capitalization, book-to-market ratio, profitability, investment, dividends-to-book ratio, market beta, and the stock's return over the past 12 months, excluding the most recent month. All seven variables are motivated by evidence from prior work cited earlier. For example, Koijen and Yogo (2019) use essentially the same variables, except for the last one, which is motivated by Gompers and Metrick (2001). In the intensive-margin model, non-ESG characteristics also include w_{mn}, the stock's weight in the market portfolio of covered stocks, as dictated by the model. The intensive model thus includes two different measures related to stock size. All variables are computed from CRSP and Compustat data. Their precise definitions are in the Online Appendix.

Some of the non-ESG stock characteristics, such as market capitalization, exhibit signif-

[11] Environmental greenness equals $-(10 - E\_score_{i,t-1}) \times E\_weight_{i,t-1}/100$. E_score is "Environmental Pillar Score," a number between zero and 10 measuring a company's resilience to long-term environmental risks. E_weight is "Environmental Pillar Weight," a number between zero and 100 measuring the importance of E relative to S and G in the company's industry. As Pástor, Stambaugh, and Taylor (2022) explain, interacting pillar scores and weights in this way is important for producing a meaningful measure of greenness.

icant skewness. Therefore, instead of using their raw values, we employ their cross-sectional percentiles. For consistency, we also use cross-sectional percentiles of stocks' E, S, and G greenness values, as well as of the stock's ESG composite score. In short, both sets $\mathcal{G}$ and $\mathcal{C}$ contain the cross-sectional percentiles of stocks' characteristics rather than raw values. Finally, we use cross-sectional percentiles also to compute $\mathcal{G}_0$, which contains the values of the ESG characteristics for the market portfolio. For each characteristic, we compute its value-weighted average across all covered stocks, then we set the corresponding element of $\mathcal{G}_0$ to that average's percentile in the cross section of stocks.

4.2. Total ESG tilts

The solid line in Panel A of Figure 1 displays quarterly estimates of T from equation (10) computed across all sample 13F institutions, i.e., the aggregate ESG-related tilt. The series begins at 6.9% in 2012, drops as low as 5.2% in 2016, and ends at 6.5% in 2023. In other words, the dollar amount of ESG-related effects in each institution's stock holdings, summed across institutions, has consistently been about 6% of the institutions' total AUM.

Recall that our estimation approach controls for numerous non-ESG stock characteristics. If we rerun our approach without including those controls, the estimate of T is substantially larger, attributing too much to ESG effects. In 2023, for example, that alternative estimate is 11.5%, more than three-fourths too high. This result underscores the importance of controlling for non-ESG characteristics when computing ESG-related tilts.

As noted earlier, $\mathcal{G}$ includes three ESG characteristics per stock—cross-sectional percentiles of the E, S, and G greenness measures. To complement this baseline analysis, we re-estimate the model with $\mathcal{G}$ containing only one ESG characteristic: the composite ESG score, also expressed as a cross-sectional percentile. The resulting estimates of T are substantially smaller. In 2023, for example, our estimate of T that allows the three ESG dimensions to matter individually is 1.7 times the estimate based on the composite. A single ESG score thus fails to capture the full extent of ESG-related tilts. The three dimensions of ESG are distinct, and institutions differ in how much importance they assign to each dimension.

Panel A of Figure 1 also displays estimates of the aggregate tilts at the intensive and extensive margins, defined in equations (11) and (12). The extensive-margin tilt is typically around 2%, while the intensive-margin tilt is two to four times higher.

The greater role for the intensive-margin tilt could in principle be driven by institutions holding many stocks. After all, the extensive-margin tilt of an institution holding every stock (e.g., a total market index fund) is zero. Our aggregate tilts are AUM-weighted, and large institutions tend to hold more stocks. To investigate, we construct two counterparts of Panel A of Figure 1, where instead of aggregating tilts across all institutions, we aggregate them within two subsets. The first subset includes institutions that hold an above-median number of stocks in the given quarter, while the second subset includes institutions with a below-median number of holdings, typically fewer than 100.[12] (The plots are in the Online Appendix.) We find that all tilts are substantially smaller for the first subset of institutions, which is not surprising, as larger institutions tend to tilt less. More importantly, for both subsets of institutions, the intensive-margin tilt always exceeds the extensive-margin tilt. Specifically, for the first subset, the intensive-to-extensive tilt ratio varies from 2.1 to 6.4 across quarters, while for the second subset it varies from 1.2 to 2.1. So, even for institutions holding relatively few stocks, the intensive-margin tilt is substantially higher than the extensive-margin tilt. Therefore, our finding of a greater role for the intensive-margin tilt is not driven just by institutions that hold many stocks.

Table 1 reports fourth-quarter values, year by year, of the tilts plotted in Figure 1, along with bootstrapped standard errors.[13] In general, the standard errors for aggregate tilt measures are small. For example, the standard errors for the overall tilt measure T are at most 0.002, while the estimates of T are typically at least 25 times larger. A key reason behind the low standard errors is diversification of estimation error across institutions.

Our 6% headline number of the aggregate ESG tilt rests on a variety of modeling choices. As noted earlier, this number would rise if we were to leave out controls for non-ESG characteristics, and it would fall if we were to replace the E, S, and G scores with the ESG composite. It would also rise if we were to disaggregate the holdings of mutual fund families (see Section 5), but it might fall if we were to include more non-ESG characteristics beyond the seven already included. The number is also conditional on the functional forms of our extensive- and intensive-margin models as well as ESG ratings from a specific provider (see Section 4.6 for an alternative). While we find our modeling choices reasonable, we encourage the reader to view the magnitudes of our results with the customary dose of caution. We also note that our measures of ESG investing exclude any potential greening of the market portfolio (see Section 6) as well as shareholder engagement.

[12]The median number of stocks held ranges from 104 to 121 across quarters, with the overall median of 115 across institution-quarters. The 90th percentile of the number of holdings across institution-quarters is 653, less than one third of all covered stocks in our sample. Most institutions hold relatively few stocks.

[13]These standard errors lend themselves to the usual interpretation, because the 5th and 95th percentiles of the bootstrap distributions are close to the estimated tilts minus/plus twice the standard errors.

4.2.1. ESG tilts in the context of total portfolio tilts

Many discussions of ESG investing note its growing popularity over the past decade. It may therefore seem puzzling that Panel A of Figure 1 shows no clear upward trend in the aggregate ESG-related tilt. Instead, the pattern is relatively flat, with the largest estimates of T appearing both early and late in the sample period.

To understand this seeming puzzle, it is useful to note that ESG investing is not the only trend in the U.S. investment industry. Two other trends also matter in this context. First, indexing has steadily gained market share relative to active management.[14] Second, actively managed funds have become more diversified, increasingly holding more stocks and aligning more closely with benchmark weights (e.g., Pástor, Stambaugh, and Taylor, 2020). In other words, active management has been both losing market share and becoming less active, continuing the trends noted by Stambaugh (2014). These trends combine to produce a downward trend in the industry's overall portfolio tilts relative to passive benchmarks.

Given this broader decline in portfolio tilts, it is less surprising that ESG-related tilts have not increased. We suggest gauging ESG tilts within the context of this overall reduction in active tilts. A simple measure of institution i's total portfolio tilt is active share, defined by Cremers and Petajisto (2009) as

$$AS_i = \frac{1}{2} \sum_{n=1}^{N} |w_{in} - w_{mn}| \ . \tag{32}$$

Active share varies both over time and across institutions. Panel A of Figure 2 displays the AUM-weighted average of active share for the institutions in our sample. Consistent with a decline in tilts generally, this series exhibits a steady downward trend, falling from 0.42 to 0.30 between 2012 and 2023.[15] This fall in total tilts represents a headwind to institutions' ESG tilts. Panel B of Figure 2 plots time series of cross-sectional percentiles in active share. The 5th percentile hovers around 0.3, while the 95th percentile is consistently near the maximum value of 1.0. This large dispersion in active share reflects heterogeneity in institutions' investment approaches. For example, institutions with a large presence in indexing tend to have low active shares. Given their weaker propensity to tilt overall, such

[14]For example, among equity mutual funds and ETFs, index funds' ownership of the U.S. stock market increased from 9% to 18%, while active fund's ownership share dropped from 19% to 13% between 2013 and 2023 (see the Investment Company Institute's *2024 Investment Company Fact Book*, page 29).

[15]A steady decline in active share has been reported by Cremers and Petajisto (2009), Stambaugh (2014), Koijen, Richmond, and Yogo (2022), and others. Koijen et al. argue that most of this decline is due to capital flows from active to passive investors rather than strategies becoming more passive.

institutions typically have relatively low ESG tilts, too.[16]

To account for overall tilts, we divide each institution's ESG tilt by its concurrent active share. We then compute an AUM-weighted average of these ratios and plot the resulting aggregate, essentially a scaled version of T, in Panel B of Figure 1. In contrast to Panel A, the scaled T trends clearly upward, especially after 2016. Adjusting for active share thus presents a different picture of ESG investing's importance over time: even though ESG tilts are not a growing share of AUM, they are a growing share of total portfolio tilts. The latter share doubles between 2016 and 2023, reaching 27% by the end of our sample.

4.3. Green and brown portfolio tilts

Next, we separate green tilts from brown. For any given dimension of ESG, such as E or the composite ESG score, we compute the various tilts defined in Section 2.4. For example, by taking AUM-weighted averages of T_i^G and T_i^B defined via equations (17) through (19), we compute the aggregate green and brown tilts, T^G and T^B, respectively. In this section, we examine the empirical patterns in green and brown tilts both across investors and over time, considering both extensive and intensive margins.

Figure 3 plots the time series of T^G (Panel A) and T^B (Panel B). Each panel displays these tilts computed using four alternative scales to classify greenness: E, S, G, and the composite ESG score. There are three main findings. First, T^G always exceeds T^B, indicating that financial institutions as a whole tilt green throughout the sample period. Second, T^G trends upward whereas T^B is fairly constant, implying that institutions are becoming increasingly green. Third, all of these patterns are similar across the four greenness measures.

If 13F-filing institutions tilt green, other investors must tilt brown (see equation (23)). We illustrate this point in Figure 4. Our sample institutions' positive and increasing green-minus-brown (GMB) tilt is plotted as the solid line in each of the four panels, with each panel based on one of the four greenness measures. The dashed line shows the GMB tilt of non-13F filers, taken collectively as one quasi-institution. Non-13F filers include households and institutions below the $100 million filing threshold for Form 13F. This segment of stockholders has tilted brown and increasingly so, balancing the green tilt of the 13F-filers.

Some of the most vocal dialogue surrounding ESG investing calls for institutions to

[16] In an earlier version of this paper, we present regression evidence showing a significant positive relation between institutions' ESG tilts and their active shares, across both time and institutions.

divest from brown stocks.[17] Such divestment is the component of green tilt that we denote as underweighting brown stocks (equation (14)). In this context, divestment includes both avoidance of brown stocks and reduction of existing positions. Figure 5 shows that divestment at the intensive margin (Panel A) is consistently larger than divestment at the extensive margin (Panel B). In other words, most divestment is partial, reducing brown stocks' weights, as opposed to total divestment that eliminates holdings. This finding is consistent with the theory of Edmans, Levit, and Schneemeier (2024), in which full divestment can be suboptimal from the perspective of a responsible investor, because it does not incentivize firms to mitigate their externalities. We find that, unlike the extensive margin, the intensive one rises substantially over time, especially from 2017 to 2022.

4.4. Which institutions are greener?

In this section, we analyze how greenness varies across institutions with respect to institutional characteristics such as size, type, and location. We begin with institution size.

In Figure 6 we plot the AUM-weighted average GMB tilt separately for large, medium, and small institutions, grouped by AUM terciles. For each of the four greenness measures, large institutions exhibit positive and mostly increasing GMB tilts. In other words, large institutions are green, and increasingly so. In contrast, the GMB tilts of medium and small institutions are often negative and mostly decreasing. In essence, the 13F filers' positive and growing GMB tilt, observed earlier in Figure 4, owes to just the largest institutions.

The world's largest institution, BlackRock, increasingly emphasized sustainability in the late 2010s. This emphasis culminated in January 2020, when BlackRock declared that sustainability should be its new standard for investing (BlackRock, 2020). After 2020, BlackRock's emphasis on sustainability waned. In line with these public stances, BlackRock's GMB tilt grew rapidly in the 2010s for all four measures of greenness, peaked in 2020, and declined afterwards. For example, based on the ESG composite, BlackRock's tilt rose from nil in 2013 to 9% of AUM in 2020, before dropping to 5.5% of AUM by 2023. BlackRock's GMB tilt outpaced its large-institution counterpart, which reached 4.2% of AUM in 2020 (see Panel A of Figure 6). Nonetheless, even when we exclude BlackRock from the large-institution group, the remaining institutions in that group still display a positive and rising GMB tilt for all four greenness measures. Similarly, when we exclude the "Big Three" institutions—BlackRock, State Street, and Vanguard—from the large-institution group, the

[17] For example, in 2020, the world's largest asset manager, BlackRock, announced that it would exit investments in thermal coal producers, and the world's largest sovereign wealth fund, that of Norway, fully divested from oil and gas explorers and producers.

remaining large institutions have a positive and increasing GMB tilt. The main patterns in Figure 6 are thus robust to the exclusions of BlackRock and the Big Three. See the Online Appendix for details.

We also explore whether characteristics other than AUM relate to an institution's GMB tilt. First, we entertain differences across types of institutions, as classified by prior studies including Bushee (2001) and Bushee, Carter, and Gerakos (2014). Following those studies, we classify institutions as (i) investment advisors, (ii) banks, (iii) insurance companies, or (iv) pensions/endowments.[18] By both institution count and AUM, the bulk of sample institutions are investment advisors, with banks a distant second. Second, we consider whether an institution has signed the UNPRI. We download the list of signatories and signature dates from the UNPRI website. We merge these data with our sample by using institution name and combining fuzzy matching, manual checks, and web searches. Finally, we determine each institution's geographical location based on the 13F filings and manual checks.

Table 2 reports the estimates from panel regressions of institutions' GMB tilts on a number of explanatory variables that include UNPRI, institution-type, and location dummies as well as the institution's active share and log AUM. We also include a time trend, by itself and interacted with log AUM. Across the columns, we show specifications with no fixed effects, with time fixed effects, and with institution fixed effects. Results including both fixed effects are in the Online Appendix; they are very similar to the results based on institution fixed effects only. When including fixed effects, we omit explanatory variables as appropriate (e.g., no institution-type dummies when including institution fixed effects).

A number of significant relations appear in Table 2. With either no fixed effects or time fixed effects, AUM exhibits a strongly significant positive relation to greenness. Since the time trend is constructed to equal zero in 2023, the result indicates that larger institutions are greener at the end of the sample period. The positive coefficient on the interaction term indicates that the relation betwen AUM and greenness strengthens over time. These results are robust across greenness measures, with just two exceptions (the AUM coefficient when greenness is measured by E and the interaction-term coefficient when greenness is measured by G). Estimates in the first column imply that increasing AUM from its 33rd percentile to its 67th percentile is associated with a 3.2 percentage point (pp) increase in GMB tilt in 2023 and a 1.6 pp decrease in GMB tilt in 2012.[19] These relations, including their reversal

[18]We are grateful to Brian Bushee for providing these data on his website. Following Bushee et al. (2014), we combine the categories Investment Company and Independent Investment Advisor into a single category; we combine Public Pension Funds and University and Foundation Endowments into a single category; and we omit institutions classified as Miscellaneous.

[19]The difference in log(AUM) between the two percentiles is 1.40. Note that 0.032 equals 1.40×0.0229,

over time, are consistent with the patterns in Figure 6.

UNPRI signatories have significantly greener tilts. This relation holds strongly across institutions (i.e., in specifications with time fixed effects), for all four greenness measures. The relation has the same estimated sign also within institutions (i.e., in specifications with institution fixed effects), but it is significant only for the E measure of greenness, indicating that an institution becomes environmentally greener after signing UNPRI. Across institutions, UNPRI signatories' GMB tilts are higher by a sizable 1.8–4.7 pp. The regressions' low R^2 values, however, suggest that UNPRI status is far from a perfect indicator of an institution's greenness. Moreover, these simple regressions do not establish any causal relation. Nonetheless, it seems useful to document that institutions that sign a commitment to invest responsibly tilt their portfolios toward greener stocks.

GMB tilts also differ significantly across the four institution types. F-tests strongly reject equality of tilts across institution types, except for the E measure of greenness. Depending on the specification, banks' GMB tilts are 2.9–14.0 pp lower than those of insurance companies (the omitted type), and the difference is significant for each greenness measure except E. Banks are also browner than both investment advisors and pensions/endowments. In most specifications, insurance companies are the greenest institution type.

In the Online Appendix, we show the time series of GMB tilts by institution type. For all four types, including banks, the GMB tilt is mostly positive and growing over the sample period. The positive GMB tilt for banks may seem surprising, given the evidence discussed in the previous paragraph. The reason behind it is that the type-level GMB tilts are computed by AUM-weight-averaging the GMB tilts of institutions within the given type. While a typical bank is brown, the largest banks are green (recall the positive coefficients on AUM in Table 2), and their greenness disproportionately affects the AUM-weighted average.

As also shown by Table 2, European institutions are significantly greener than U.S. ones (the omitted category). More precisely, European institutions' holdings of U.S. stocks are greener than U.S. institutions' holdings of U.S. stocks, as measured by GMB tilts. Depending on the specification, European institutions' GMB tilts are 3.5-5.2 pp higher than those of U.S. institutions. The GMB tilts of institutions located in the rest of the world are between those of European and U.S. institutions.

For comparison, Koijen, Richmond, and Yogo (2022) find that non-U.S. investors have a higher demand for stocks with higher E scores but lower G scores. They also find differences in demand elasticities for E and G scores across institution types. However, they use a dif-

and -0.016 equals $1.40 \times [0.0229 - 0.44 \times 0.0779]$, where -0.44 is the value of Trend in 2012.

ferent methodology and different data; for example, their E scores come from Sustainalytics and their G scores reflect the number of entrenchment provisions. Atta-Darkua et al. (2022) find that European investors who are members of the CDP (formerly the Carbon Disclosure Project) have been decarbonizing their portfolios faster than other investors.

Table 3 explores whether the above patterns in GMB tilt are driven by its green or brown leg. We estimate similar panel regressions replacing the dependent variable T_i^{GMB} with either T_i^G or T_i^B.[20] We see that both green and brown tilts drive the positive relation between AUM and greenness, but brown tilts matter much more. At the end of our sample period, larger institutions are both slightly greener and much less brown. Both legs, green and brown, contribute to the widening gap in GMB tilts between large and small institutions. The roles of time trends, UNPRI status, and institution type are similarly strong, but opposite in sign, for green and brown tilts. Finally, active share has a strong, positive relation to both green and brown tilts. The GMB tilt exhibits no relation to active share, however, as the positive effects in the green and brown legs largely offset each other (Table 2).

4.5. Industry adjustment

Our ESG characteristics are based on MSCI ESG ratings, which are not industry-adjusted. ESG ratings vary across industries—for example, E ratings tend to be higher in finance, health care, and technology, and lower in chemicals, steel, and mining (see Table 2 in Pástor, Stambaugh, and Taylor, 2022). We focus on unadjusted ratings because they are widely used and reflect how many investors approach ESG, particularly those who exclude entire industries, such as oil and gas, from their portfolios. That said, some investors assess ESG performance relative to industry peers. In this section, we examine portfolio tilts based on industry-adjusted ESG scores.

We classify each firm into one of 94 industries, quarter by quarter, using MSCI's industry classification. For each of E, S, G, and the composite ESG score, we compute the average greenness of each industry in each quarter by computing the value-weighted average of g_n across all firms in that industry and quarter. We then compute each firm n's industry-adjusted score in each quarter as g_n minus the corresponding industry average. We convert both the industry-adjusted values and the industry average to percentiles in the full cross section of stocks, analogous to our main analysis. Finally, we treat the industry-adjusted ESG scores' percentiles as our ESG characteristics ($\mathcal{G}$), and we add the industry-average

[20]Table 3 reports results from regressions without fixed effects. Results with fixed effects are in the Online Appendix. Results with time fixed effects are very similar to those reported in Table 3.

ESG scores' percentiles to the set of controls ($\mathcal{C}$).

Figure 7 is the counterpart of Figure 1 using industry-adjusted ESG scores. The resulting total ESG tilt, T, remains fairly stable over time, ranging mostly from 4% to 5%. This range is below that of the unadjusted T (5.2% to 6.9%; see Figure 1), suggesting that more investors use raw scores than industry-adjusted scores when forming portfolios. Apart from their lower levels, the adjusted tilts closely resemble the unadjusted ones: in both figures, T^{int} far exceeds T^{ext}, with the former trending slightly upward and the latter downward. The key takeaway from both figures is the same: ESG tilts account for a modest share of AUM and are much larger on the intensive margin.

Figure 8 mirrors Figure 3 but uses industry-adjusted green and brown tilts. Again, the levels are lower compared to the unadjusted tilts, but the overall patterns remain similar. In both figures, green tilts exceed brown, green tilts trend upward while brown tilts are flat, and these patterns hold across the four greenness measures. Industry-adjusted or not, institutions collectively tilt green, and increasingly so. In the Online Appendix, we show the industry-adjusted versions of the remaining figures and tables for the institutional sample.

4.6. Sustainalytics ratings

While MSCI is the leading global provider of ESG ratings (see Section 4.1), investors have access to multiple data sources. In this section, we assess the robustness of our results by using ESG scores from one of MSCI's main competitors: Sustainalytics.

Our Sustainalytics sample is smaller than our MSCI sample, for two reasons. First, MSCI covers more than twice as many firms. Second, we use Sustainalytics data only from December 2018 onward, following a major methodology overhaul that year. ESG ratings from the two providers are positively correlated, with correlations ranging from 0.17 for G scores to 0.78 for E scores. For a detailed description of the Sustainalytics data, including data coverage and summary statistics, see the Online Appendix.

We use Sustainalytics' ESG scores to re-estimate all portfolio tilts for our institutional sample. We report all of our main results—the counterparts of Figures 1 through 6 and Tables 1 through 3—in the Online Appendix. These results are remarkably similar to those based on MSCI scores. For example, the aggregate tilt is stable over time, ranging from 5.9% to 6.7%. The aggregate intensive-margin tilt remains much larger than the extensive-margin tilt. Green tilts exceed brown, indicating that institutions as a whole tilt green. Divestment from brown stocks still occurs primarily at the intensive margin. Larger institutions tilt greener for three of the four greenness measures. UNPRI signatories and European institutions are also greener, significantly so for the ESG composite and E measures. To summarize, all of our main conclusions hold also when using Sustainalytics' ESG scores.

5. Estimates of ESG tilts: Mutual funds

In this section, we estimate ESG-related portfolio tilts for U.S. equity mutual funds. Looking at mutual funds is useful for several reasons. First, some of the institutions analyzed in Section 4 are mutual fund families. In their 13F filings, fund families aggregate the portfolio holdings of their individual funds. This aggregation could mask fund-level ESG tilts that offset within families, understating the extent of overall tilting. It could also understate extensive-margin tilts, because a stock excluded by some funds will still appear in family-level holdings if held by any fund of the same family. Analyzing fund-level holdings allows us to address both issues and assess their importance. It also enables us to examine the tilts of ESG-labeled funds, which cannot be identified in 13F filings.

A key limitation of the mutual fund universe is that it is much smaller than financial institutions in aggregate, covering only about a quarter of the 13F sample's AUM. The mutual fund sample excludes significant holdings, especially of banks, insurers, pension funds, endowments, hedge funds, and sovereign wealth funds. As a result, mutual fund evidence cannot fully capture the extent of ESG-related tilting in the investment industry. We view the results presented in this section as complementary to our main findings in Section 4, which draw on a broader and more comprehensive institutional sample.

5.1. Data

Starting with the Thomson Reuters Mutual Fund Holdings (S12) dataset, we compute funds' quarterly portfolio weights w_{in} among the subset of covered stocks. We take data on funds' characteristics from CRSP and Morningstar Direct.

We construct the fund sample as follows. Starting from all funds in the S12 dataset, we exclude bond funds, international funds, funds of funds, real estate funds, target retirement funds, and other non-equity funds based on keywords in the Morningstar Category variable. We also exclude variable annuity funds using the CRSP flag. We include index funds, labeled as "index" or "enhanced index" by CRSP or Morningstar. We aggregate multiple share classes of the same fund and drop funds with less than \$10 million in AUM. As in the previous section, we require funds to have at least 50% of their assets in covered stocks and at least 30 holdings, and we define a fund's AUM as the total value of its covered holdings. We clean the mutual fund data following Pástor, Stambaugh, and Taylor (2020).[21]

The number of funds in our sample ranges from 1,506 in 2012 to 1,221 in 2023. Funds' combined AUM grows from $2.5 trillion to $8.3 trillion during that period. For comparison, the 13F sample studied earlier contains roughly four times as much AUM. As of 2023, index funds make up 15% of the fund sample by count and 58% by AUM.

5.2. Total ESG tilts

Figure 9 plots aggregate ESG tilts—T, T^{int}, and T^{ext} from equations (10) through (12)—based on three mutual fund samples. The first sample includes only active funds, excluding index funds. The second sample includes all funds, active and passive. The third sample includes mutual fund families, which we create by grouping funds into families based on family names obtained from Morningstar (or CRSP if unavailable). For each family, we combine the holdings of member funds into a single "quasi-fund" and estimate its tilt.

Panel A of Figure 9 shows total ESG tilts, T, across the three samples. For active funds, T is stable, ranging from 10% to 13%. Including passive funds lowers T to 6%–10%, reflecting their much smaller tilts. Fund-family tilts are lower still, between 3.5% and 6%. The gap between the T values for all funds and for fund families, which ranges from 1.6 to 4.2 percentage points, captures the extent of within-family offsetting. These offsets modestly reduce overall tilts. For example, at the end of our sample, T is 6.5% for all funds and 4.7% for fund families, so that offsetting tilts account for 1.8% of mutual fund families' AUM. Multiplying this share by the fraction of institutional AUM held by mutual fund families implies that adjusting for within-family offsets would increase the aggregate tilt in Figure 1 by just under 0.5% in 2023.[22] This adjustment, from 6.5% to 7%, is fairly small.

Panels B and C of Figure 9 plot intensive- and extensive-margin tilts, T^{int} and T^{ext}. The values of T^{ext} for the all-fund sample are about three times larger than those for the fund-family sample, and they also exceed their counterparts for the broader institutional sample

[21] During the cleaning process, we correct one additional, notable, recently-introduced error in the S12 dataset. One data-cleaning step involves excluding funds whose total holdings exceed twice their fund-level assets. This step mistakenly drops the world's largest mutual fund, Vanguard's Total Stock Market Index Fund, starting in 2020q4. In the S12 data, this fund's reported asset values are misreported by a factor of ten from 2020q4 onward. After we correct this data error, the fund is restored to our sample.

[22] Mutual fund families manage $8.3 trillion in 2023, which represents 26.3% of the AUM of all institutions in our 13F sample. Multiplying 26.3% by 1.8% gives 0.47%.

(see Figure 1). This is expected, as stock exclusions are more common at the fund level than at the family level, as explained earlier. More importantly, for each sample and each point in time, $T^{ext} < T^{int}$, just like in Figure 1. In other words, our finding that $T^{ext} < T^{int}$ obtains not only at the institution level but also at the fund level.

5.3. Green and brown portfolio tilts

Figure 10 plots green and brown tilts, T^G and T^B, for the all-fund sample. The figure mirrors Figure 3, but with tilts estimated at the mutual fund level rather than the institution level. As in Figure 3, though to a lesser extent, we observe $T^G > T^B$, indicating that mutual funds collectively tilt green. Unlike in Figure 3, there is no upward trend in T^G (or T^B), suggesting that the gradual increase in green tilting is driven by non-mutual-fund institutions. Green tilts range from 3% to 8%; brown tilts from 2% to 6%. All patterns in Figure 10 look similar across the four greenness measures.

Figure 11 examines mutual funds' divestment from brown stocks, paralleling Figure 5 but using the all-fund sample instead of the full institutional sample. Extensive-margin divestment is larger for funds—ranging mostly from 0.5% to 1.5%, compared to 0.1% to 1.3% for institutions—reflecting the greater prevalence of full divestment at the fund level. More notably, as in the institutional sample, intensive-margin divestment remains consistently larger, typically from 1.5% to 3%, and it exceeds extensive-margin divestment throughout. Intensive- exceeds extensive-margin divestment even for active funds, where one might expect the latter divestment to be largest, as active funds typically hold fewer stocks than passive funds (see the Online Appendix). Thus, even for individual mutual funds, brown divestment is primarily partial rather than full.

5.4. Which funds are greener?

Table 4 reports results from panel regressions of mutual funds' green and brown tilts on three fund characteristics—AUM, active share, and an ESG-label dummy—along with a time trend and its interaction with AUM. These regressions are analogous to those in Table 3, but they exclude institution-level regressors and include a fund-specific ESG dummy. This indicator, sourced from Morningstar, equals one if the fund is described in its prospectus or other regulatory filings as focusing on ESG, sustainability, or impact investing. We estimate the regressions separately for all mutual funds (Panel A) and for active funds only (Panel B). As the results are similar across panels, we discuss them jointly.

Table 4 shows that both green and brown tilts are strongly and positively related to active share, echoing the institution-level results in Table 3. Green tilts are also positively related to the time trend and its interaction with AUM, though these effects are somewhat weaker than in Table 3. Unlike in Table 3, the negative relations between brown tilts and both AUM and its interaction with the time trend are not statistically significant.

The most novel findings in Table 4, with no counterpart in Table 3, concern the ESG dummy. Compared to non-ESG funds, ESG-labeled funds' green tilts are substantially larger, by 9–16 pp of AUM, and their brown tilts are 2–5 pp smaller. Both of these relations are highly statistically significant across all four greenness measures. The relations are economically large relative to funds' aggregate green tilts (3–8%) and brown tilts (2–6%), plotted in Figure 10. These results indicate that tilting, as captured by our methodology, is an important feature of mutual funds' ESG investment strategies.

6. ESG investing versus index investing

We distinguish ESG investing from index investing. The rationale follows Pástor, Stambaugh, and Taylor (2021): when all investors value ESG equally, they all hold the market portfolio, as their preferences are fully reflected in market weights through equilibrium prices. There is then only index investing and no ESG investing.

To say there is no ESG investing in that setting seems reasonable. For example, the standard CAPM is another setting in which all investors hold the market portfolio, even though they have a preference for low-beta stocks. In that setting, low-beta stocks have low expected returns, so they have high prices and thus large market weights, all else equal. Yet the CAPM is generally characterized as a world of index investing, not "low-beta" investing. The same logic applies when ESG preferences are fully embedded in market prices.

The market portfolio's weights depend on the average strength of ESG preferences, but without heterogeneity in those preferences, there is no ESG investing. The latter arises from differences in ESG preferences across investors. To simplify their model, Pástor, Stambaugh, and Taylor (2021) assume that ESG is the only reason investors deviate from the market portfolio. Here we allow additional stock characteristics to affect investors' portfolio choices, given our empirical focus, but we maintain the same distinction between ESG and index investing by controlling for market weights when estimating tilts.

If the average ESG preference strengthens, then, all else equal, the market portfolio will allocate more to green stocks. To investigate this possibility, for each month t we compute

$$\kappa_t = \sum_{n=1}^{N_{t-1}} (w_{mn,t} - w_{mn,t-1}) g_{n,t-1} \, , \tag{33}$$

where N_{t-1} is the number of stocks in our covered universe at the beginning of the month, and $w_{mn,s}$ is proportional to stock n's market capitalization, summing to 1 across stocks for s equal to both $t-1$ and t. The value of κ_t is positive (negative) if market weights reallocate toward green (brown) stocks during month t.

Figure 12 plots the cumulative sum of κ_t for each of our four greenness measures. For the ESG composite, the cumulative reallocation falls during the first half of the sample period, but then it rises sharply, by 5.5 percentage points, between mid-2018 and mid-2020. By the end of the sample period, the cumulative reallocation reaches 2.1%. The end-of-sample value is very similar when we measure greenness by the G score, although the reallocation to G-friendly stocks follows a different path. In contrast, the market reallocates away from S-friendly stocks over the full sample period, despite a steady reallocation toward them between 2015 and 2021. Finally, the reallocation to E-friendly stocks increases steadily between 2012 and 2020, before pulling back slightly at the end. Overall, for greenness measured by E, the market portfolio's allocation to green stocks increases substantially, by 7.6 percentage points, during the sample period.

7. Conclusion

The total amount of ESG investing is smaller than commonly suggested. ESG-related tilts in institutional equity portfolios account for about 6% of the institutions' equity AUM, an order of magnitude less than the 76% of industry AUM managed by UNPRI signatories. The ESG tilt has been fairly steady from 2012 to 2023. However, institutions' overall portfolio tilts, as measured by active share, have declined over this period. When scaled by active share, the typical institution's ESG tilt has doubled over seven years, reaching 27% in 2023. ESG tilts are thus more than one-quarter the size of total portfolio tilts.

Our approach to estimating ESG tilts has several advantages. First, it isolates tilts toward stocks' ESG characteristics after controlling for non-ESG characteristics. This is valuable because the two sets of characteristics are correlated. For example, an institution may hold Tesla's stock either for its environmental profile or because it likes holding large-cap growth stocks. Our approach separates the two motives. Second, our approach allows the three dimensions of ESG to enter separately, recognizing, for example, that investors may assess Tesla's environmental virtues separately from Tesla's treatment of its employees. We find that using only a composite ESG score misses over 40% of the tilts associated with the E, S, and G characteristics. Third, our approach breaks down ESG tilts into components capturing the extensive and intensive margins. We find significant ESG tilts at both margins, but the intensive-margin tilts are two to four times larger.

Our approach also allows us to separate green tilts from brown. We find that institutions as a whole tilt more green than brown, and increasingly so. The rise in net green tilting occurs primarily at the intensive margin; for example, institutions divest from brown stocks mostly by reducing positions rather than eliminating them. In contrast, non-13F institutions and households tilt more brown than green, and increasingly so. Greenness also varies across institutions. Larger institutions are greener, and the rise in net green tilting is fully driven by the largest third of institutions. Those institutions are increasingly green, whereas smaller institutions are increasingly brown. UNPRI signatories and European institutions are also greener, while banks are the least green institutional type. Our results are similar across four different ESG-related measures of greenness. These results are important because green tilts likely impose a financial cost, as noted earlier.

While our primary analysis relies on ESG scores from MSCI, we obtain similar results using Sustainalytics data. Results are also similar when using industry-adjusted ESG scores, though the resulting ESG tilts are even smaller, between 4% and 5% of AUM.

We also estimate the ESG-related tilts of U.S. equity mutual funds. We find only small offsetting ESG tilts within fund families. Mutual funds' aggregate ESG tilts range from 6% to 10%, and up to 13% for active funds. Extensive-margin tilts are larger than for institutions but remain smaller than intensive-margin tilts. Divestment of brown stocks also remains smaller at the extensive margin, indicating that even at fund level, brown divestment is more partial than full. Mutual funds collectively tilt green, though less so than institutions. Finally, ESG-labeled funds exhibit much larger green tilts, and much smaller brown tilts, than non-ESG funds.

Our study opens many avenues for future research. For example, do institutions substitute voting green for tilting green, or are those actions complementary?[23] How large are the financial costs incurred by institutions with green tilts? Could one compute stock-level ESG tilts and relate them to stocks' expected returns? One could also apply our methodology to measure portfolio tilts with respect to non-ESG characteristics as well as tilts in other asset classes, such as bonds, bank loans, and private equity.

[23]A growing literature compares the effectiveness of exit and voice strategies at curtailing firms' anti-social behavior. For a recent example of an empirical comparison, see Saint-Jean (2023).

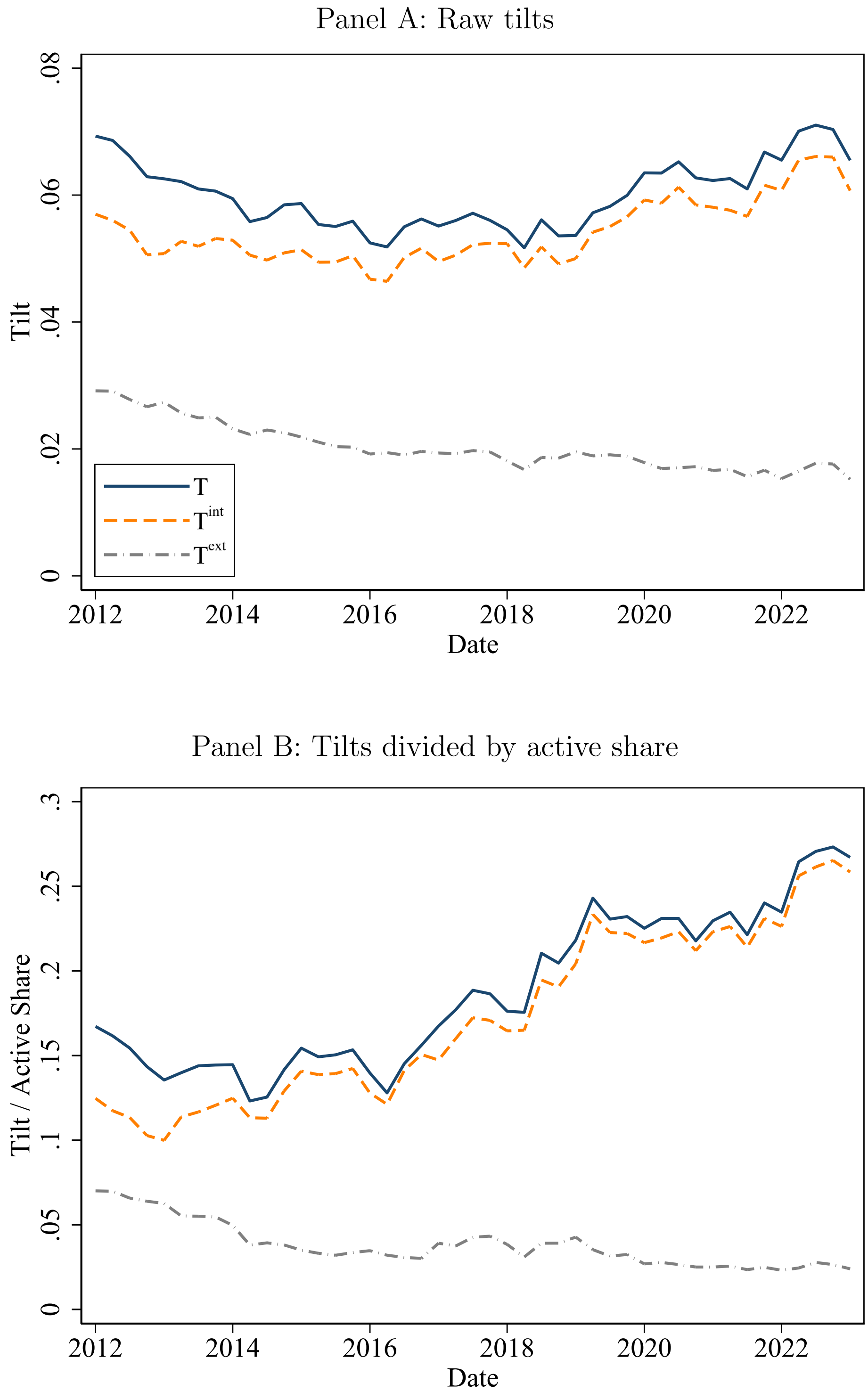


Figure 1. Total, intensive, and extensive ESG tilts. Panel A plots the aggregate ESG-related tilt (T) and its decomposition into intensive and extensive tilts, T^{int} and T^{ext}, respectively. In Panel B, we divide each institution's tilt by its active share and then plot the AUM-weighted average of the resulting quantities. Tilt estimates are from the specification in which $\mathcal{G}$ contains three ESG characteristics (E, S, and G) per stock. Tick marks are at the fourth quarter of each year.

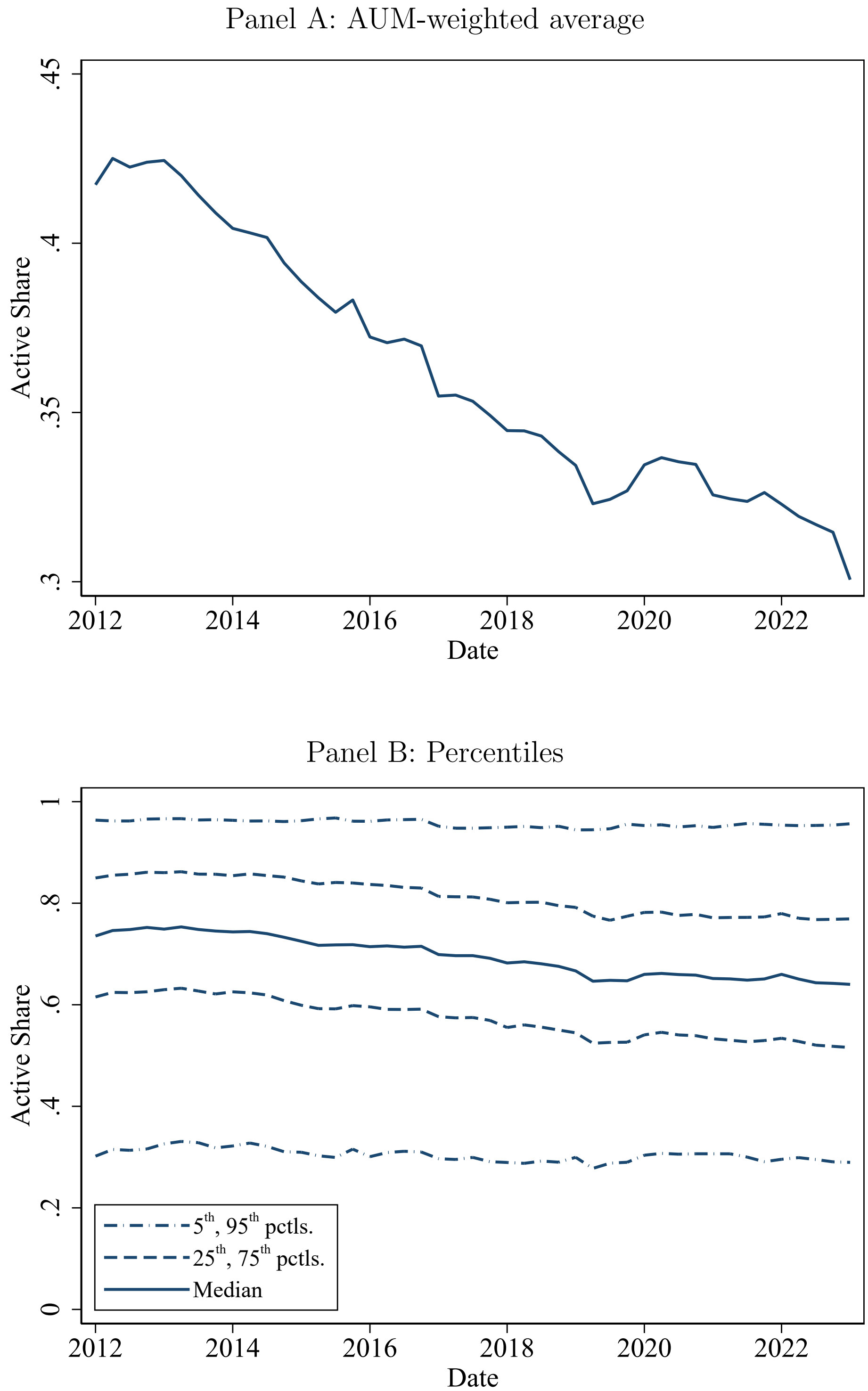


Figure 2. Active share. Panel A plots the AUM-weighted average of institutions' active share. Panel B plots the cross-sectional percentiles of active share.

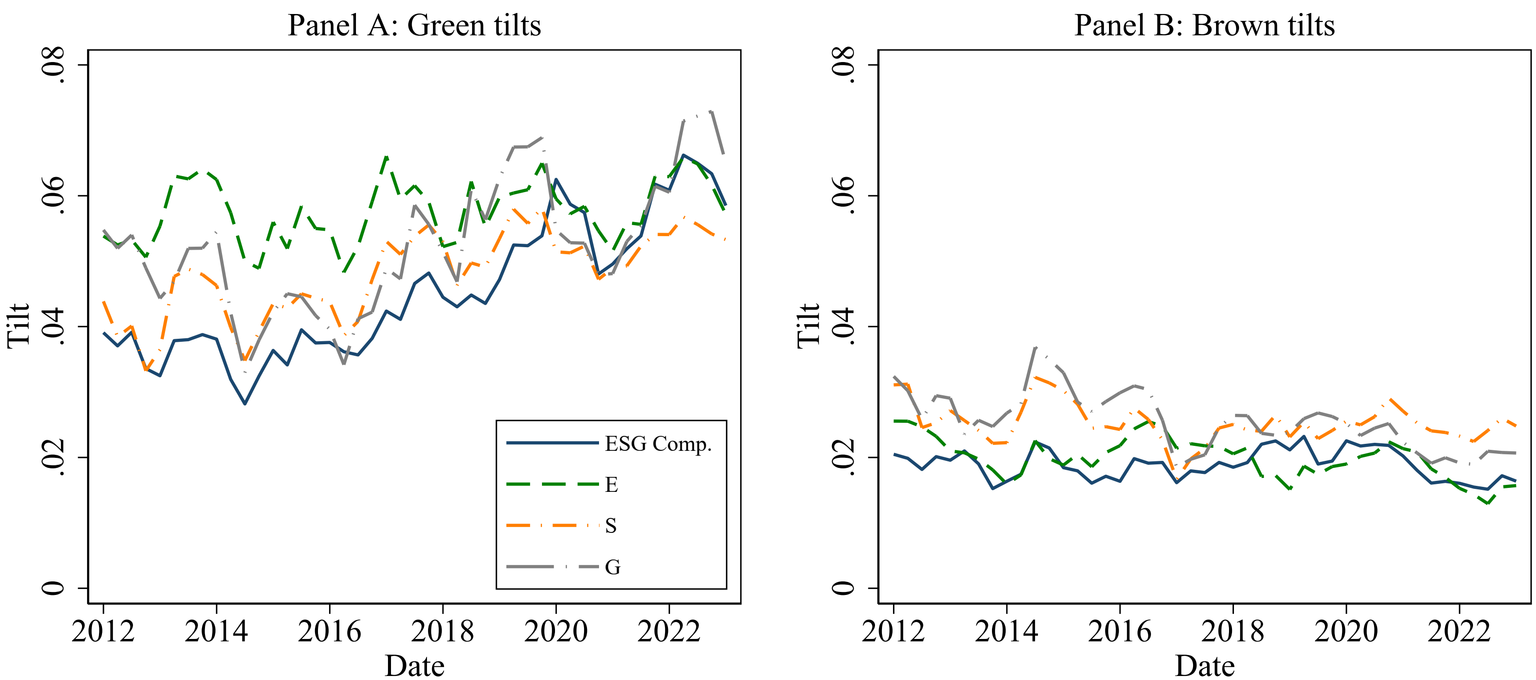


Figure 3. Green and brown tilts. The green and brown tilts for the ESG composite are from the model specification with a single ESG characteristic per stock. The other three pairs of tilts are from the specification with three ESG characteristics per stock, changing one of the three characteristics to its neutral value while holding the other two characteristics at their sample values. We plot the AUM-weighted average of the tilts.

Figure 4. GMB tilts of 13F filers and non-filers. The solid line shows the AUM-weighted average of GMB tilt across sample 13F institutions. The dashed line shows the same quantity for non-13F investors, which we treat as a single quasi-institution whose dollar holding of each stock equals the stock's market capitalization minus the combined holdings of the stock by 13F institutions (including those not in our sample). In Panel A, $\mathcal{G}$ contains just the composite ESG score, so tilts are computed from the model specification with a single ESG characteristic per stock. In Panels B through D, g_n is a stock's E, S, or G component, and tilts are computed from the specification with $\mathcal{G}$ containing three ESG characteristics per stock.

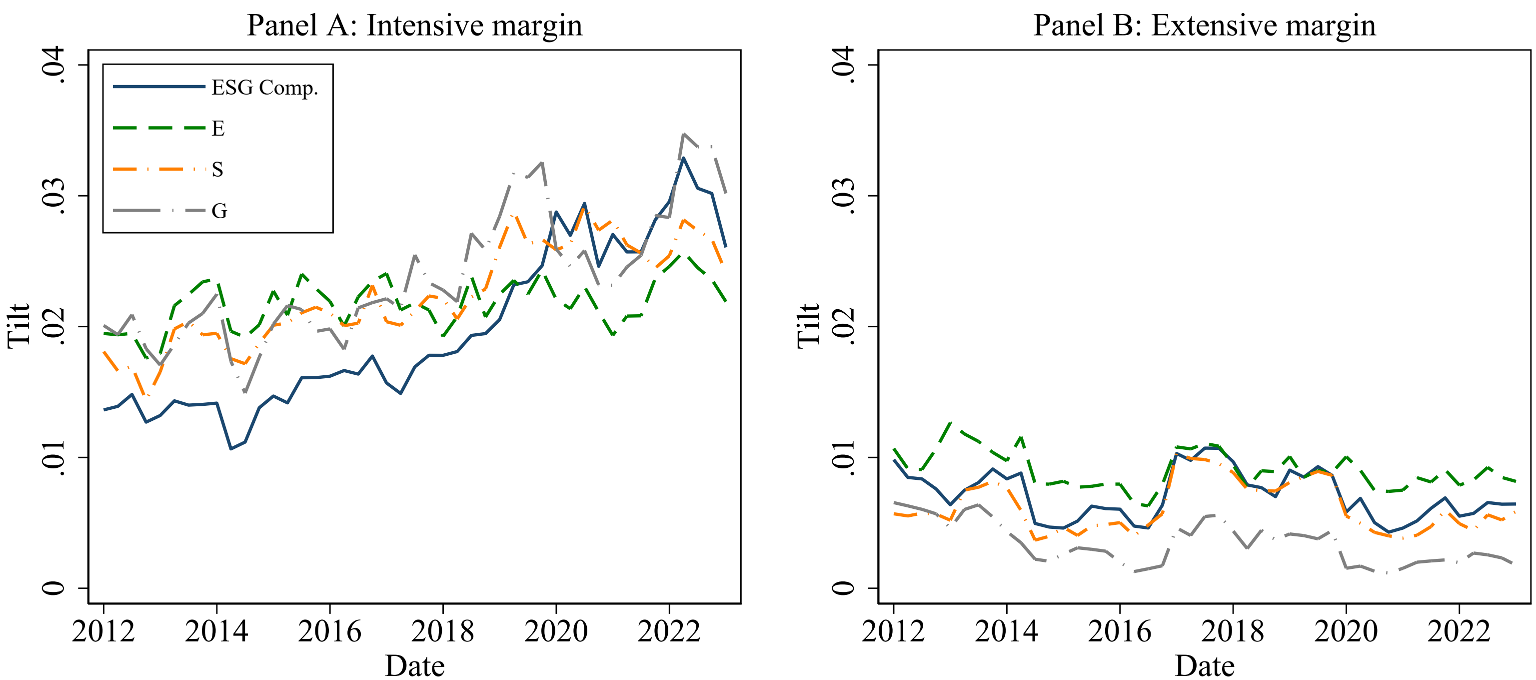


Figure 5. Divestment from brown stocks. Divestment from brown stocks, which is a component of green tilt, can be done on either the extensive margin (full divestment) or intensive margin (partial divestment). We show both. Panel A shows the component of intensive green tilts coming from under-weighting brown stocks. Panel B shows the component of the extensive green tilts coming from under-weighting brown stocks. Tilts using the ESG composite are from the model specification with a single ESG characteristic per stock, and other tilts are from the specification with three ESG characteristics per stock. We plot the AUM-weighted average of the tilts.

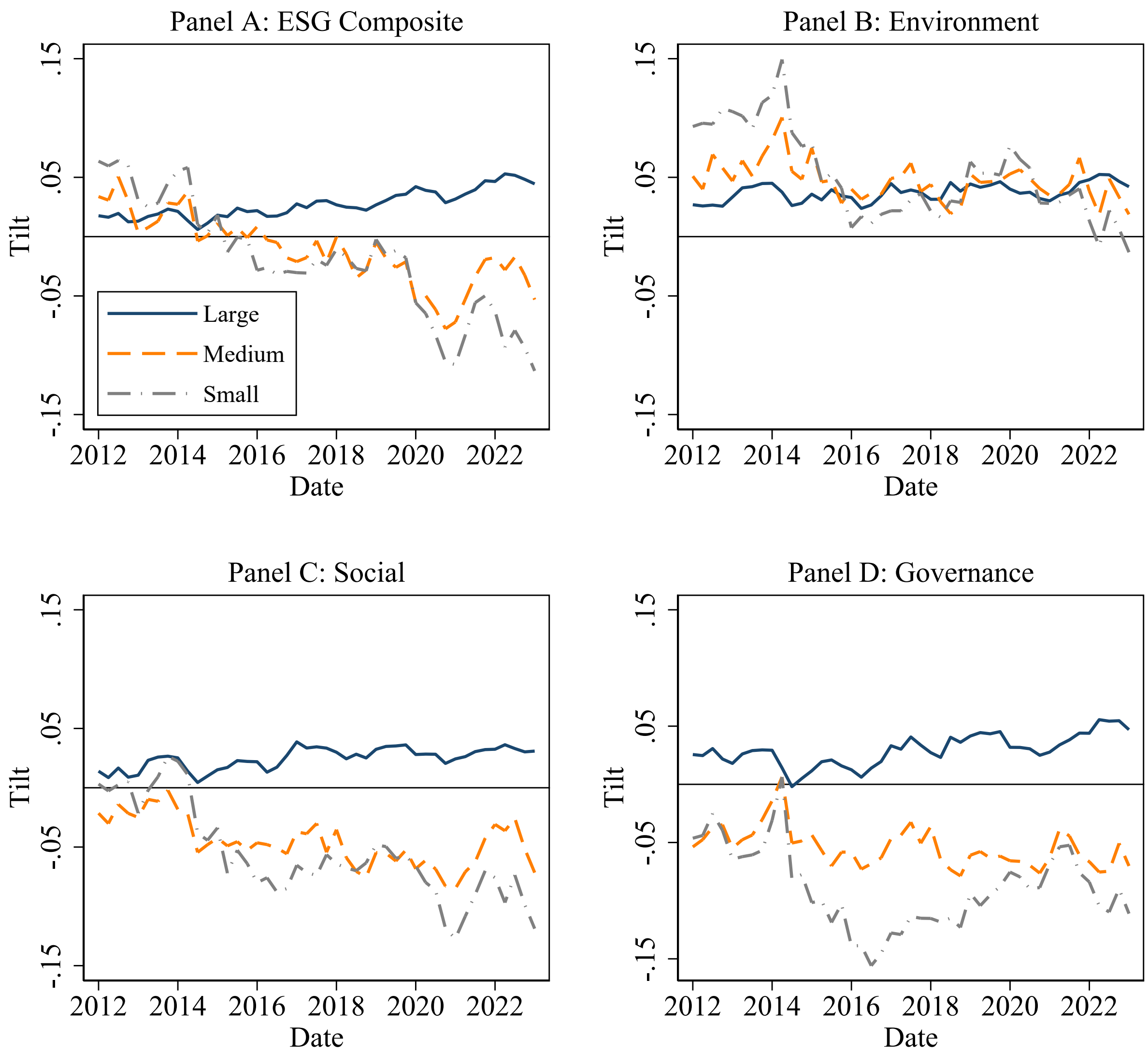
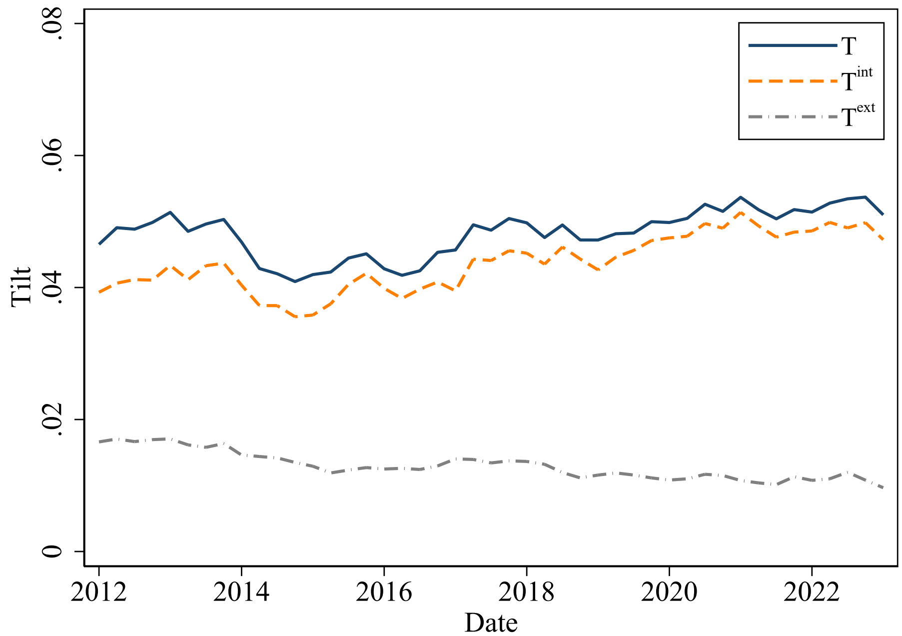


Figure 6. Institution size and greenness. This figure compares GMB tilts across subsamples formed based on quarterly AUM terciles. Each line shows the subsample's AUM-weighted average GMB tilt.

Panel A: Raw tilts



Panel B: Tilts divided by Active Share

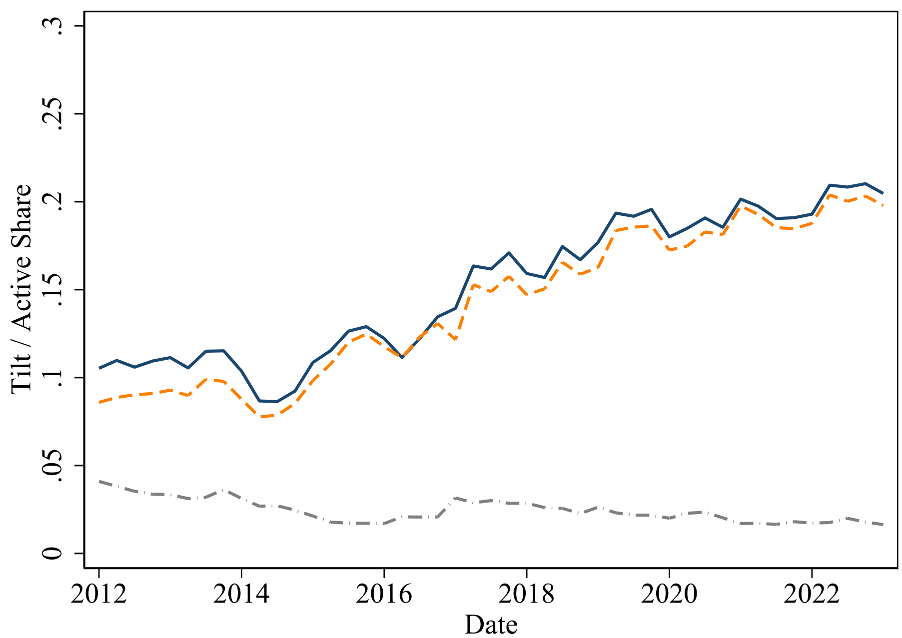


Figure 7. Industry-adjusted tilts. This figure plots versions of the tilts from Figure 1 estimated using stocks' industry-adjusted ESG scores. For each of E, S, and G, we compute stocks' industry-adjusted scores as g_n minus the value-weighted average of g_n across stocks in the same industry and quarter. We convert the industry average and industry-adjusted values to percentiles in the full cross section of stocks, similar to our main analysis. We include in $\mathcal{G}$ the industry-adjusted E, S, and G scores' percentiles, and we add the three industry-average E, S, and G scores' percentiles to the set of exogenous controls. Otherwise, the method and data are the same as in our main analysis.

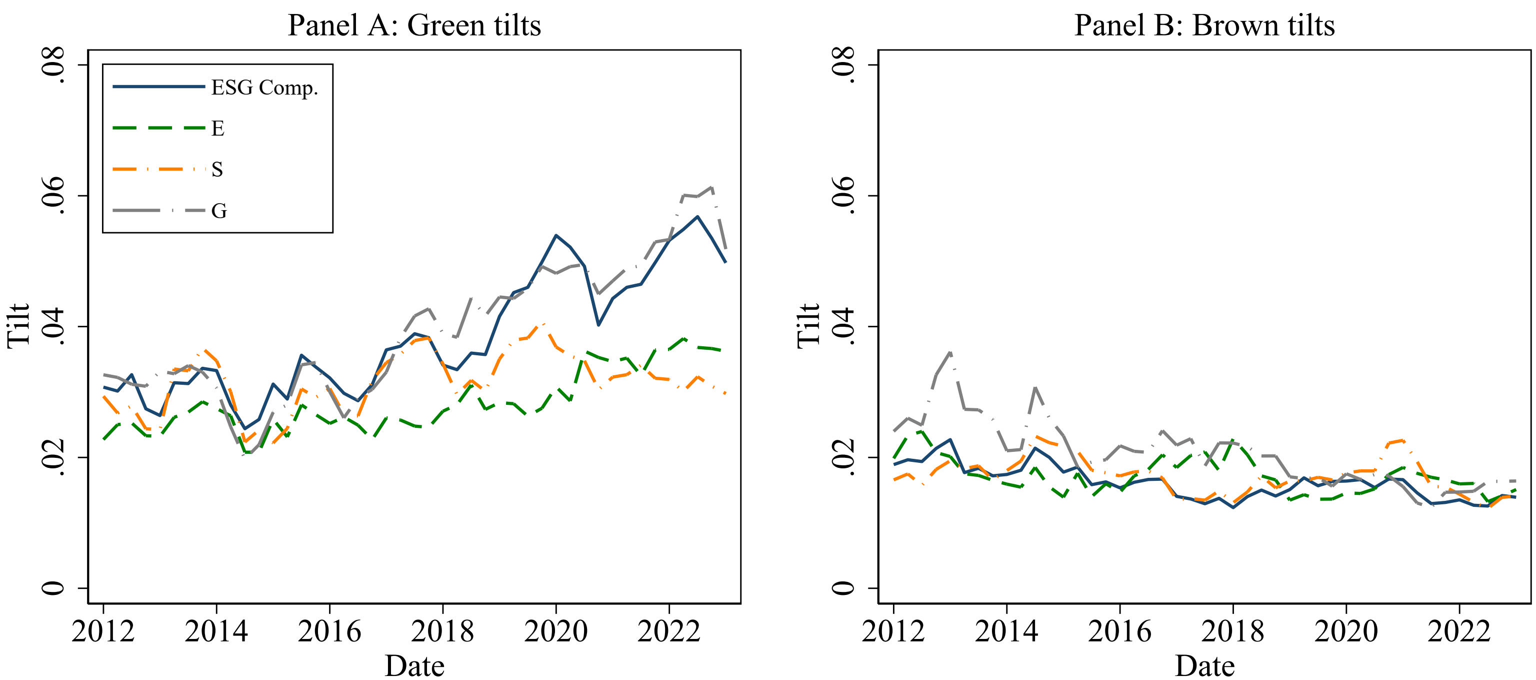


Figure 8. Industry-adjusted green and brown tilts. This figure plots versions of the tilts from Figure 3 estimated using stocks' industry-adjusted ESG scores. Details on the method are the same as in Figure 7.

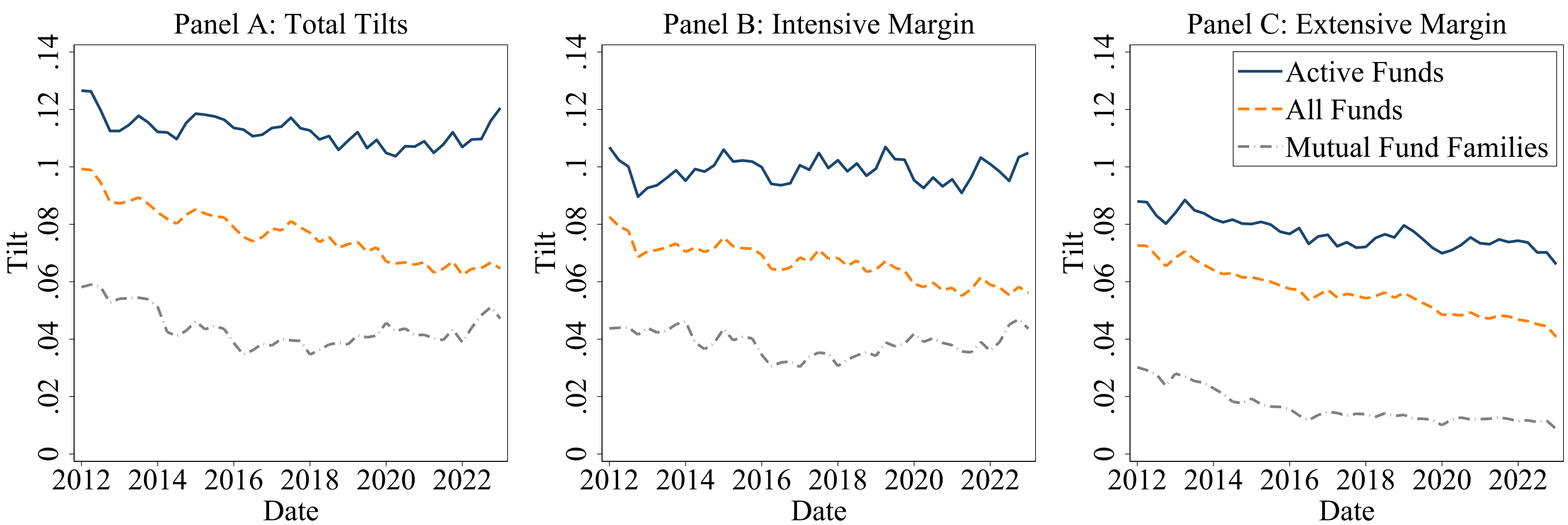


Figure 9. Mutual funds' ESG tilts. Panels A, B, and C plot the aggregate ESG-related tilt (T), intensive-margin tilt (T^{int}), and extensive-margin tilt (T^{ext}), respectively, estimated in mutual-fund samples indicated in the legend. The sample of all funds includes both active and passive funds. We create the sample of mutual fund families as follows. For each family, we construct a "quasi-fund" by aggregating all funds (active and passive) within each family into a single portfolio, and we estimate that quasi-fund's tilts. All lines show AUM-weighted averages of tilts within the given sample of mutual funds. Tilt estimates are from the specification in which $\mathcal{G}$ contains three ESG characteristics (E, S, and G) per stock.

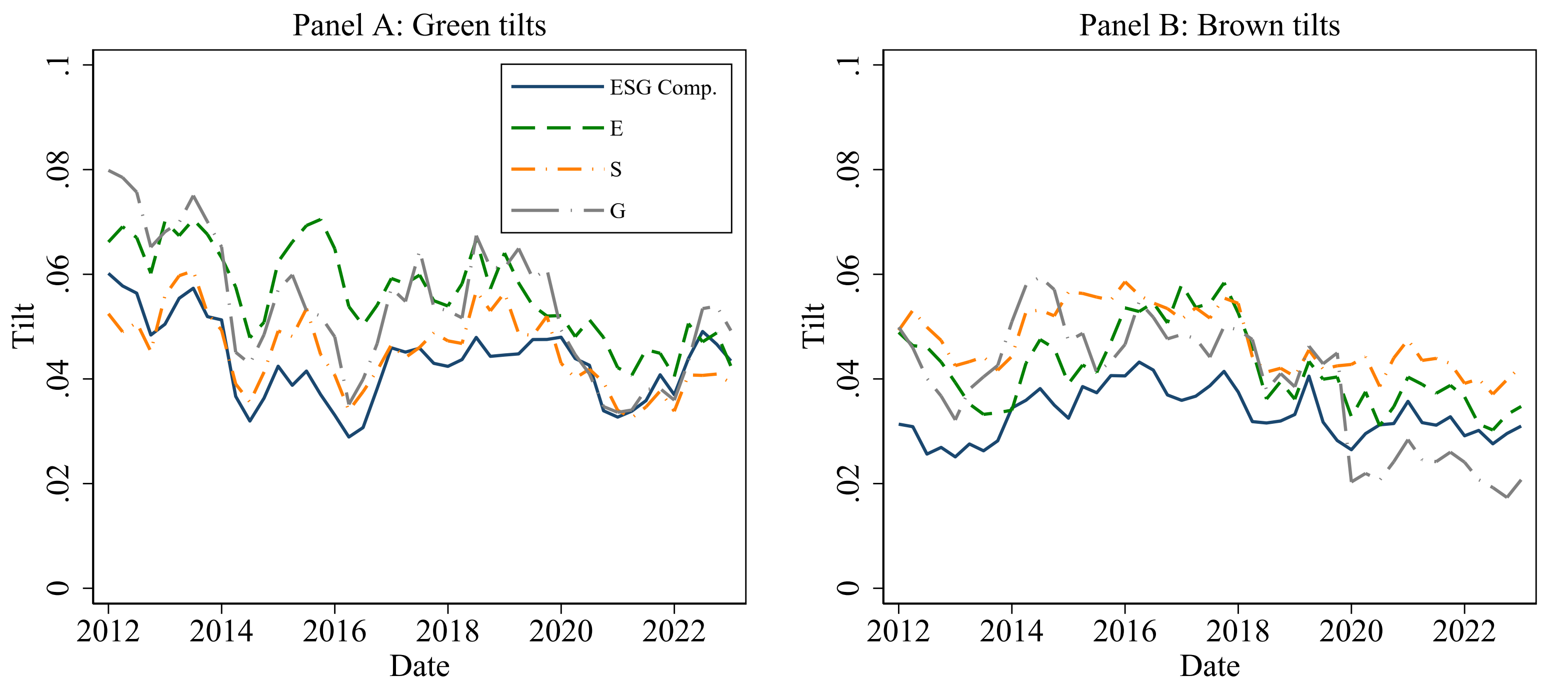


Figure 10. Mutual funds' green and brown tilts. This figure plots the same quantities as Figure 3, but tilts are estimated at the level of individual mutual funds (both active and passive).

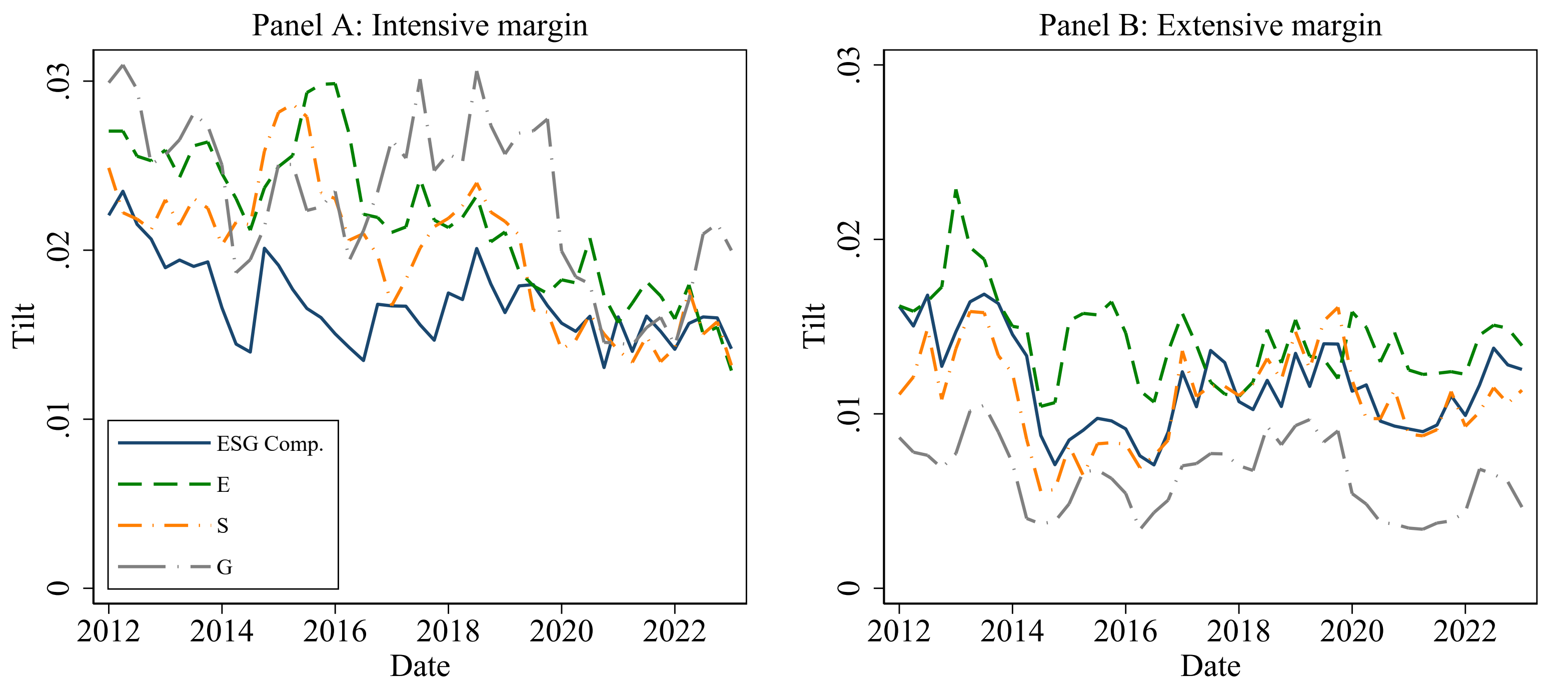


Figure 11. Mutual funds' divestment from brown stocks. This figure plots the same quantities as Figure 5, but tilts are estimated at the level of individual mutual funds (both active and passive).

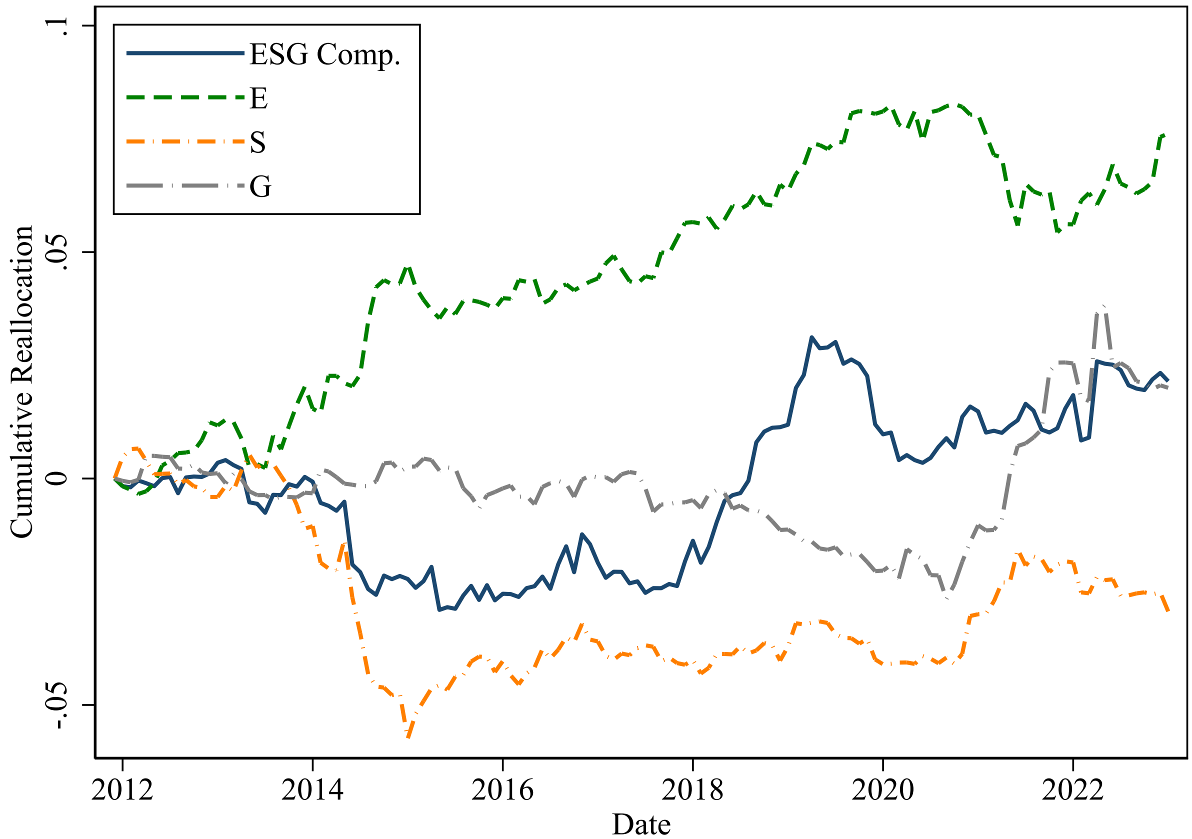


Figure 12. Market reallocation to green stocks. This figure plots the cumulative sum of κ_t, defined in equation (33). Equivalently, it plots the cumulative change in the fraction of stocks whose greenness, g_n, is less than the value-weighted mean of g_n across all stocks. A positive (negative) change corresponds to the market placing greater (less) weight on green stocks relative to brown. The figure shows results with four versions of g_n: the composite ESG score as well as its separate E, S, and G components.

Table 1
Aggregate tilts

This table shows estimated aggregate tilts from each year's fourth quarter. Tilts are estimated from the specification in which $\mathcal{G}$ contains three ESG characteristics (E, S, and G) per stock. Columns 2 to 4 report the estimated tilts, and columns 5 to 7 show the bootstrapped standard errors. Tilts are expressed as a fraction of institutions' aggregate covered AUM.

	Estimated Tilt			Standard Error		
Year	Total	Intensive	Extensive	Total	Intensive	Extensive
2012	0.069	0.057	0.029	0.002	0.002	0.001
2013	0.063	0.051	0.027	0.002	0.002	0.001
2014	0.059	0.053	0.023	0.002	0.002	0.001
2015	0.059	0.051	0.022	0.002	0.002	0.001
2016	0.052	0.047	0.019	0.002	0.002	0.001
2017	0.055	0.050	0.019	0.002	0.002	0.001
2018	0.055	0.052	0.018	0.002	0.002	0.001
2019	0.054	0.050	0.020	0.002	0.001	0.001
2020	0.063	0.059	0.018	0.002	0.002	0.001
2021	0.062	0.058	0.017	0.001	0.001	0.001
2022	0.065	0.061	0.015	0.002	0.002	0.001
2023	0.065	0.061	0.015	0.001	0.001	0.000

Table 2: Which institutions are greener?

This table shows results from panel regressions with the dependent variable equal to the institution's GMB tilt, T_{it}^{GMB}. The greenness measure is noted in the column headers. All regressions use 100,357 institution×quarter non-missing observations from 2012q4–2023q4. AUM is divided by the total market capitalization of all covered stocks. Trend equals the observation's quarter minus 2023q4, divided by 100, so Trend is increasing over time, zero at the end of the sample, and negative in preceding quarters. We compute active share as in Cremers and Petajisto (2009). 1(UNPRI) is an indicator for whether the institution signed the UNPRI on or before the given quarter. Institution types are from Bushee et al. (2014), with 1(Insurance) the excluded category. Institution locations are from the 13F filings, with 1(United States) the excluded category. Robust t-statistics clustered by institution are in parentheses. The regression R^2 as well as the R^2 from a regression with fixed effects only are shown at the bottom. The last row contains p-values testing whether the coefficients are equal across the four institution-type indicators (Insurance, Inv. advisor, Bank, and Pension/endowment).

	No Fixed Effects				Time Fixed Effects				Institution Fixed Effects			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0229	0.0043	0.0245	0.0179	0.0231	0.0056	0.0251	0.0194	0.0085	-0.0157	0.0111	-0.0020
	(8.50)	(1.42)	(7.48)	(6.91)	(8.56)	(1.85)	(7.64)	(7.53)	(1.46)	(-2.24)	(1.55)	(-0.34)
log(AUM) × trend	0.0779	0.0428	0.0513	0.0031	0.0803	0.0486	0.0551	0.0100	0.0652	0.0347	0.0471	0.0020
	(8.19)	(3.87)	(4.66)	(0.33)	(8.41)	(4.37)	(4.98)	(1.06)	(5.98)	(2.93)	(3.86)	(0.18)
Trend	0.6341	0.3585	0.4315	0.0276					0.5056	0.2303	0.3996	0.0150
	(6.53)	(3.18)	(3.85)	(0.28)					(4.79)	(1.97)	(3.36)	(0.14)
Active share	-0.0012	-0.0119	0.0138	-0.0459	-0.0016	-0.0120	0.0128	-0.0461	-0.0094	-0.0511	0.0410	-0.0383
	(-0.07)	(-0.58)	(0.63)	(-2.52)	(-0.10)	(-0.58)	(0.58)	(-2.53)	(-0.22)	(-1.00)	(0.80)	(-0.90)
1(UNPRI)	0.0452	0.0453	0.0473	0.0196	0.0452	0.0438	0.0469	0.0180	0.0261	0.0500	0.0190	0.0008
	(4.64)	(4.09)	(4.28)	(2.22)	(4.63)	(3.96)	(4.25)	(2.04)	(1.75)	(2.86)	(1.21)	(0.06)
1(Inv. advisor)	-0.0244	0.0019	-0.0058	-0.0214	-0.0246	0.0020	-0.0058	-0.0213				
	(-1.68)	(0.10)	(-0.24)	(-0.99)	(-1.69)	(0.11)	(-0.24)	(-0.98)				
1(Bank)	-0.0855	-0.0292	-0.1398	-0.0623	-0.0858	-0.0291	-0.1399	-0.0624				
	(-4.28)	(-1.36)	(-4.39)	(-2.47)	(-4.29)	(-1.35)	(-4.39)	(-2.47)				
1(Pension/endowment)	-0.0128	-0.0135	0.0211	0.0059	-0.0128	-0.0134	0.0210	0.0059				
	(-0.75)	(-0.58)	(0.78)	(0.24)	(-0.75)	(-0.58)	(0.78)	(0.24)				
1(Europe)	0.0345	0.0502	0.0514	0.0377	0.0349	0.0510	0.0521	0.0386				
	(2.49)	(3.27)	(3.25)	(2.89)	(2.51)	(3.30)	(3.30)	(2.96)				
1(Rest of world)	0.0113	0.0381	0.0224	0.0112	0.0118	0.0395	0.0233	0.0128				
	(0.75)	(2.23)	(1.22)	(0.66)	(0.79)	(2.31)	(1.26)	(0.76)				
R^2	0.020	0.005	0.023	0.016	0.023	0.008	0.025	0.019	0.436	0.446	0.497	0.406
R^2 (FEs only)	N/A	N/A	N/A	N/A	0.009	0.003	0.004	0.003	0.432	0.444	0.496	0.406
p (Inst. types equal)	0.000	0.122	0.000	0.004	0.000	0.122	0.000	0.004	N/A	N/A	N/A	N/A

Table 3: Institutions' green and brown tilts

This table shows results from panel regressions with dependent variable equal to the institution's green tilt (T^G_{it}, columns 1–4) or brown tilt (T^B_{it}, columns 5–8). There are no fixed effects. Remaining details are the same as in Table 2.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0025	-0.0024	0.0037	0.0038	-0.0204	-0.0067	-0.0208	-0.0140
	(1.84)	(-1.22)	(2.13)	(3.08)	(-11.46)	(-4.13)	(-9.69)	(-7.84)
log(AUM) × trend	0.0230	0.0270	0.0156	0.0029	-0.0550	-0.0160	-0.0356	-0.0002
	(4.33)	(3.71)	(2.52)	(0.63)	(-9.39)	(-2.73)	(-5.19)	(-0.03)
Trend	0.2431	0.2653	0.2078	0.0564	-0.3912	-0.0944	-0.2233	0.0288
	(4.45)	(3.57)	(3.22)	(1.17)	(-6.62)	(-1.58)	(-3.24)	(0.45)
Active share	0.0904	0.1439	0.1283	0.0939	0.0916	0.1552	0.1143	0.1396
	(10.01)	(11.03)	(11.38)	(10.45)	(8.52)	(13.34)	(7.77)	(11.24)
1(UNPRI)	0.0230	0.0225	0.0122	0.0020	-0.0223	-0.0229	-0.0350	-0.0176
	(3.74)	(2.95)	(1.81)	(0.43)	(-4.09)	(-4.29)	(-5.47)	(-3.08)
1(Inv. advisor)	-0.0030	0.0063	0.0048	-0.0163	0.0215	0.0045	0.0107	0.0052
	(-0.33)	(0.43)	(0.48)	(-1.58)	(2.79)	(0.52)	(0.60)	(0.33)
1(Bank)	-0.0171	-0.0121	-0.0303	-0.0298	0.0685	0.0171	0.1095	0.0325
	(-1.72)	(-0.77)	(-2.71)	(-2.59)	(5.16)	(1.57)	(4.45)	(1.79)
1(Pension/endowment)	-0.0055	-0.0077	0.0104	-0.0054	0.0073	0.0057	-0.0108	-0.0113
	(-0.57)	(-0.47)	(0.86)	(-0.46)	(0.74)	(0.47)	(-0.58)	(-0.65)
1(Europe)	0.0272	0.0388	0.0281	0.0271	-0.0072	-0.0114	-0.0233	-0.0105
	(2.87)	(3.55)	(2.61)	(3.57)	(-0.97)	(-1.45)	(-2.70)	(-1.32)
1(Rest of world)	0.0097	0.0258	0.0151	0.0139	-0.0016	-0.0124	-0.0074	0.0026
	(1.08)	(2.19)	(1.40)	(1.56)	(-0.19)	(-1.43)	(-0.68)	(0.25)
R^2	0.017	0.024	0.023	0.014	0.043	0.030	0.043	0.037
p (Inst. types equal)	0.085	0.060	0.000	0.013	0.000	0.389	0.000	0.014

Table 4: Mutual funds' green and brown tilts

This table shows results from panel regressions with dependent variable equal to the mutual fund's green tilt (T_{it}^G, columns 1–4) or brown tilt (T_{it}^B, columns 5–8). Variable 1(ESG-labeled fund), obtained from Morningstar, is an indicator for whether the fund is described in the prospectus or other regulatory filings as focusing on sustainability, impact investing, or ESG factors. Panel A shows results using all mutual funds (passive and active); this sample includes 28,789 fund×quarter non-missing observations from 2018q4–2023q4. (We begin the sample in 2018q4 because this is the first quarter that 1(ESG-labeled fund) is available.) Panel B shows results using active mutual funds only; this sample includes 24,788 fund×quarter non-missing observations from 2018q4–2023q4. Other details are the same as in Table 3.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
				Panel A: All funds				
log(AUM)	-0.0002	-0.0028	-0.0010	0.0011	-0.0019	-0.0000	-0.0011	-0.0031
	(-0.09)	(-1.14)	(-0.49)	(0.71)	(-1.24)	(-0.02)	(-0.57)	(-1.94)
log(AUM) × trend	0.0252	0.0412	0.0339	0.0282	-0.0048	-0.0161	-0.0034	-0.0079
	(1.90)	(2.31)	(2.25)	(2.10)	(-0.45)	(-1.24)	(-0.27)	(-0.60)
Trend	0.3598	0.5525	0.4306	0.2055	-0.0057	-0.2302	-0.0761	-0.2480
	(2.48)	(2.93)	(2.62)	(1.40)	(-0.05)	(-1.62)	(-0.54)	(-1.70)
Active share	0.0862	0.0642	0.1108	0.1011	0.0269	0.1362	0.0722	0.0584
	(10.58)	(5.56)	(10.59)	(13.08)	(3.87)	(12.90)	(7.85)	(7.38)
1(ESG-labeled fund)	0.1395	0.1581	0.1118	0.0896	-0.0203	-0.0437	-0.0385	-0.0193
	(9.78)	(9.49)	(7.62)	(7.55)	(-3.43)	(-8.13)	(-6.21)	(-2.77)
R^2	0.075	0.054	0.051	0.050	0.006	0.039	0.014	0.015
				Panel B: Active funds				
log(AUM)	0.0006	-0.0012	-0.0005	0.0018	-0.0016	-0.0007	-0.0012	-0.0033
	(0.31)	(-0.41)	(-0.21)	(0.99)	(-0.88)	(-0.31)	(-0.52)	(-1.70)
log(AUM) × trend	0.0365	0.0618	0.0464	0.0385	-0.0054	-0.0238	-0.0074	-0.0137
	(2.23)	(2.85)	(2.51)	(2.36)	(-0.41)	(-1.49)	(-0.47)	(-0.85)
Trend	0.4914	0.8119	0.5789	0.3182	-0.0021	-0.3374	-0.1109	-0.3271
	(2.70)	(3.46)	(2.80)	(1.74)	(-0.01)	(-1.89)	(-0.64)	(-1.78)
Active share	0.0968	0.0311	0.1272	0.1214	-0.0103	0.1543	0.0449	0.0318
	(8.04)	(1.75)	(8.43)	(10.43)	(-0.89)	(10.02)	(3.16)	(2.52)
1(ESG-labeled fund)	0.1453	0.1678	0.1170	0.0956	-0.0233	-0.0475	-0.0415	-0.0208
	(9.31)	(9.62)	(7.16)	(7.21)	(-3.42)	(-7.85)	(-5.91)	(-2.60)
R^2	0.070	0.049	0.047	0.046	0.003	0.031	0.006	0.007

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Appendix

A.1. Green and brown tilts net to zero across all investors

In this section, we prove the statement in equation (23), namely, that the green and brown tilts aggregated across all investors are always equal: $T^G = T^B$.

For each investor i, define $\phi_i = A_i/A$, where $A = \sum_j A_j$ is total AUM across all investors. Each stock n's market portfolio weight is given by $w_{mn} = M_n/M$, where M_n is stock n's market capitalization and $M = \sum_j M_j$ is total market capitalization across all stocks. Note that $A = M$. Also note that $w_{in} = M_{in}/A_i$, where M_{in} is the dollar amount of stock n held by investor i. Therefore, for each stock n,

$$\sum_i \phi_i w_{in} \;=\; \sum_i \frac{A_i}{A}\frac{M_{in}}{A_i} = \sum_i \frac{M_{in}}{A} = \sum_i \frac{M_{in}}{M} = \frac{M_n}{M} = w_{mn}, \tag{A.1}$$

with the sums taken across all investors. Taking conditional expectations of both sides of equation (A.1), we obtain

$$\sum_i \phi_i \mathrm{E}\{w_{in}|\mathcal{G},\mathcal{C}\} = \sum_i \phi_i \mathrm{E}\{w_{in}|\mathcal{G}_0,\mathcal{C}\} = w_{mn}, \tag{A.2}$$

treating the ϕ_i's as known and noting that w_{mn} is included in $\mathcal{C}$. Recalling the definition of Δ_{in} from equation (1), equation (A.2) immediately implies that

$$\sum_i \phi_i \Delta_{in} = 0 \tag{A.3}$$

for all n. That is, each stock's AUM-weighted tilt is zero. Let $\mathcal{S}_G$ denote the set of all green stocks. For any green stock n, note from the definitions in equations (13) through (16) that $\Delta_{in} = \Delta_{in}^{OG} + \Delta_{in}^{UG}$. Summing both sides of equation (A.3) across all green stocks, using the definitions in (17), we obtain

$$\begin{aligned} 0 \;&=\; \sum_{n\in\mathcal{S}_G}\left(\sum_i \phi_i \Delta_{in}\right) = \sum_i \phi_i \sum_{n\in\mathcal{S}_G} \Delta_{in} = \sum_i \phi_i \sum_{n\in\mathcal{S}_G}\left(\Delta_{in}^{OG} + \Delta_{in}^{UG}\right) = \sum_i \phi_i \left(T_i^{OG} - T_i^{UG}\right) \\ &=\; T^{OG} - T^{UG}, \end{aligned}$$

implying

$$T^{OG} = T^{UG}, \tag{A.4}$$

where $T^{OG} = \sum_i \phi_i T_i^{OG}$ and $T^{UG} = \sum_i \phi_i T_i^{UG}$ are the aggregate overweight-green and underweight-green tilts, respectively. Analogously, summing equations (A.3) across all brown stocks, we obtain

$$T^{OB} = T^{UB}, \tag{A.5}$$

where $T^{OB} = \sum_i \phi_i T_i^{OB}$ and $T^{UB} = \sum_i \phi_i T_i^{UB}$. We thus obtain the desired equation (23):

$$T^G = T^B, \tag{A.6}$$

where $T^G = \sum_i \phi_i T_i^G$ and $T^B = \sum_i \phi_i T_i^B$ are the aggregate green and brown tilts, respectively. The last step follows from recognizing that $T^G = T^{OG} + T^{UB}$ and $T^B = T^{OB} + T^{UG}$, based on equations (18) and (19). $\square$

A.2. Estimating the intensive-margin model

This section extends the discussion from Section 3.2 by providing a detailed justification for the regression model in equation (29). We begin by specifying two desired properties of our model for the intensive margin. First, for simplicity, w_{in}^+/w_{mn} is given by a restricted linear function of stock n's characteristics:

$$\frac{w_{in}^+}{w_{mn}} = \sum_{j=1}^{K} c_{ij} x_{nj}, \quad n = 1, \ldots, N. \tag{A.7}$$

That is, w_{in}^+ is linear in the K values of $w_{mn}x_{nj}$. If a given stock n is held, its expected weight could in principle depend not only on the stock's own value of $w_{mn}x_{nj}$ but also on the values of that quantity for other stocks the investor may hold. Recognizing that potential dependence, we allow c_{ij} to depend on the portfolio's expected sum across stocks of $w_{mn}x_{nj}$ (i.e., $\pi_i' h_j$, where h_j denotes the $N \times 1$ vector whose n-th element is $w_{mn}x_{nj}$). Second, for any π_i having at least one positive element, expected unconditional weights, which we denote by $\bar{w}_{in}$, always sum to one:

$$\sum_{n=1}^{N} \bar{w}_{in} = \sum_{n=1}^{N} \pi_{in} w_{in}^+ = 1. \tag{A.8}$$

Given these two properties, it can be readily verified that c_{ij} must be proportional to the reciprocal of $\sum_{n=1}^{N} \pi_{in} w_{mn} x_{nj}$. That is,

$$c_{ij} = b_{ij} \Big/ \sum_{n=1}^{N} \pi_{in} w_{mn} x_{nj}, \quad j = 1, \ldots, K, \tag{A.9}$$

where b_{ij} does not depend on X or π_i. In addition, it must be that

$$\sum_{j=1}^{K} b_{ij} = 1. \tag{A.10}$$

Substituting the right-hand side of equation (A.9) into equation (A.7) gives

$$\frac{w_{in}^+}{w_{mn}} = \sum_{j=1}^{K} b_{ij} \left(\frac{x_{nj}}{\sum_{n=1}^{N} \pi_{in} w_{mn} x_{nj}} \right). \tag{A.11}$$

For each stock held by the investor, the actual weight w_{in} obeys

$$w_{in} = w_{in}^{+} + \epsilon_{in}, \tag{A.12}$$

where ϵ_{in} has zero mean conditional on X. Combining equations (A.11) and (A.12) gives the following regression model for the stocks held:

$$\frac{w_{in}}{w_{mn}} = \sum_{j=1}^{K} b_{ij}\tilde{x}_{n,j} + e_{in}, \tag{A.13}$$

where the j-th independent variable is

$$\tilde{x}_{nj} = \frac{x_{nj}}{\sum_{n=1}^{N} \pi_{in} w_{mn} x_{nj}}. \tag{A.14}$$

The quantity $e_{in} \equiv \epsilon_{in}/w_{mn}$ satisfies the property required of a regression disturbance, i.e., that it has zero expectation conditional on the $\tilde{x}_{nj}$'s, because the n-th row of X includes w_{mn} (as noted earlier).

We estimate the regression in (A.13) using the set of stocks held by the investor. To do so, we must first construct the underlying values of $\tilde{x}_{n,j}$, which depend on π_i via equation (A.14). For that purpose we set $\pi_i = \hat{\pi}_i$, the estimate of π_i from our model of the extensive margin. We also allow for the possible correlation between e_{in} and the probability that stock n is held. Specifically, we apply a correction following Heckman (1979). The first step is to estimate the probit model,

$$y_{in} = \gamma_i' z_{in} + u_{in}, \tag{A.15}$$

where u_{in} is a standard normal variate, and investor i holds stock n if $y_{in} > 0$. We specify z_{in} as a two-element vector, with the first element equal to 1 and the second element equal to an indicator variable set to 1 if investor i held stock n during any of the previous 11 quarters (and set to 0 otherwise). The probit model is estimated via maximum likelihood using all stocks with non-missing data. The second step is to estimate the regression in equation (A.13) with the quantity $\phi(\hat{\gamma}_i{}' z_{in})/\Phi(\hat{\gamma}_i{}' z_{in})$ included as an additional independent variable, where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal density and distribution functions.[24] This regression is estimated for each institution and quarter subject to the linear coefficient restriction in equation (A.10). We find that the regressions fit the data quite well, delivering an average

[24] The use of lagged holdings in the probit model is consistent with the finding by Koijen and Yogo (2019) that an institution does not often hold a stock currently if the stock was not held within the past 11 quarters. This persistence in holdings conveniently allows us to have the probit model rely on a variable different from the x_{nj}'s used in the intensive-margin model, thereby satisfying the recommended exclusion restriction for the successful application of the Heckman correction (e.g., Puhani, 2000). If instead we were simply to specify z_{in} as containing those same x_{nj}'s, then $\phi(\hat{\gamma}_i{}' z_{in})/\Phi(\hat{\gamma}_i{}' z_{in})$ could possess strong colinearity with the x_{nj}'s, making it difficult to separate any selection effect from the primary roles of the x_{nj}'s in the intensive-margin model. We do not include lagged holdings in our extensive-margin model, because the objective of that model is to infer how stock characteristics predict the set of stocks the institution currently holds, regardless of how long the institution has held those stocks.

R^2 of 0.41 (Online Appendix). Finally, we plug the estimated b_{ij}'s into equation (A.11) to obtain expected weights for all assets, $n = 1, \ldots, N$.

The resulting values of w_{in}^{+} contain some estimation error. This error causes some estimates of w_{in}^{+} to be negative or exceed 1. We remove these implausible values by truncating w_{in}^{+} to be in [0,1]. The rate of truncation is low. Roughly 5% of w_{in}^{+} values are truncated at 0, and less than 0.5% are truncated at 1. The rate of truncation is not concentrated in any particular set of institutions (e.g., large versus small, investment advisors vs. insurance companies), nor is it concentrated in any particular industry. To show this, we regress an indicator for whether w_{in}^{+} is truncated on dummy variables for institution categories and stock industries. We find an R^2 of only 0.003, and few dummies enter significantly (Online Appendix).

After the truncation of w_{in}^{+}, the expected unconditional weights, $\bar{w}_{in}$, no longer sum to 1. We restore that property by rescaling w_{in}^{+}. Specifically, we divide $w_{in}^{+}(\mathcal{G})$ and $w_{in}^{+}(\mathcal{G}_0)$ by the investor-specific sums of $\bar{w}_{in}(\mathcal{G})$ and $\bar{w}_{in}(\mathcal{G}_0)$, respectively. After this adjustment, $\bar{w}_{in}(\mathcal{G})$ and $\bar{w}_{in}(\mathcal{G}_0)$ both sum to 1 for every investor. As a result, the sum of our estimated values of Δ_{in} across stocks is zero for each investor, as it is for the population values of Δ_{in}.

In addition, we truncate T_i^{int}, T_i^{ext} and their green and brown components to be less than 1. In 2023, this truncation affects only 0.9% of institutions that represent around 0.1% of covered AUM. No values of T_i or T_i^{GMB} exceed 1 in 2023.

A.3. Bias adjustment and standard errors

This section describes the bootstrap procedure that we use to de-bias the raw estimates of T_i and obtain their standard errors, extending the discussion from Section 3.4. We use the same procedure to de-bias all other quantities of interest (T_i^{ext}, T_i^{int}, T^{ext}, T^{int}, T_i^{G}, T_i^{B}, T_i^{GMB}, $T_i^{GMB,ext}$, $T_i^{GMB,int}$, etc.) and obtain their standard errors.

Let S denote the set of stocks with non-missing data (i.e., "covered" stocks), and let N denote the number of stocks in this set. Let K_i denote the number of covered stocks held by institution i. The bootstrap algorithm proceeds as follows, for each institution i:

1. Estimate the extensive- and intensive-margin regression models using the actual data (observed portfolio weights w_{in} and characteristics X).
   (a) For each covered stock, let $\hat{\pi}_{in}$ denote the estimated probability that institution i holds stock n, for all $n \in S$.
   (b) Let e_i denote the $K_i \times 1$ vector of estimated residuals from the intensive-margin regression (equation (A.13)), to which we have added the additional Heckman

regressor, $\phi(\hat{\gamma}_i' z_{in})/\Phi(\hat{\gamma}_i' z_{in})$ (see previous section for details). Since the intensive-margin regression is estimated with a constraint, the mean of e_i is not necessarily zero. We de-mean e_i at the institution level to be consistent with the model's assumption that $\epsilon_{in} = e_{in} w_{mn}$ has zero mean conditional on X.

   (c) Let $\hat{b}_i$ denote the intensive-margin model's estimated coefficient vector, and let $\widehat{[\rho\sigma_u]}_i$ denote the estimated coefficient on $\phi(\hat{\gamma}_i' z_{in})/\Phi(\hat{\gamma}_i' z_{in})$.

2. Motivated by the heteroskedasticity observed in the data, we allow the volatility of e_{in} to depend on stock n's market capitalization, M_n, in an institution-specific manner. Specifically, we assume the volatility of e_{in} is proportional to $M_n^{\lambda_i}$. We estimate λ_i as the coefficient on $\log(M_n)$ from an institution-specific regression of $\log(|e_{in}|)$ on $\log(M_n)$.[25] Let $\delta_{in} \equiv e_{in}/M_n^{\lambda_i}$ denote the volatility-adjusted value of e_{in}, up to a constant of proportionality. Let δ_i denote the vector of δ_{in}.

3. Compute the actual value of T_i from equation (7). Label this value T_i^{raw}.

4. Compute a simulated value of $\tilde{T}_i$ by using the following steps:

   (a) Simulate which stocks are held, $\tilde{I}_{in}$, as follows. For each of the N covered stocks in S, draw a uniform [0,1] random variable and set the indicator $\tilde{I}_{in} = 1$ if this random variable is below $\hat{\pi}_{in}$ and $\tilde{I}_{in} = 0$ otherwise. Let L_i denote the number of stocks with $\tilde{I}_{in} = 1$, which is the number of stocks held in the simulated sample. We require $L_i \geq 30$ stocks, just like in the actual data; if this condition is not met, we repeat this step until the condition is met.

   (b) With this new sample of size N, estimate the extensive-margin model while replacing the actual I_{in} with the simulated $\tilde{I}_{in}$. Denote the fitted values as $\tilde{\pi}_{in}$.

   (c) Simulate weights among the stocks held, $\tilde{w}_{in}$, as follows. For each of the L_i stocks that are held, compute w_{in}^{+}/w_{mn} from equation (A.11) while using the estimates of $\hat{b}_i$ and $\hat{\pi}_{in}$ from step 1. Following equations (A.11) and (A.13), compute a draw of $\tilde{w}_{in}/w_{mn}$ by adding two terms to w_{in}^{+}/w_{mn}. The first term is a random draw of e, which we compute as the product of $M_n^{\lambda_i}$ and a random draw (with replacement) of an element of δ_i. Multiplying by $M_n^{\lambda_i}$ performs a heteroskedasticity adjustment to e. The second term, from the Heckman adjustment, is $\widehat{[\rho\sigma_u]}_i$ times $\phi(\hat{\gamma}_i' z_{in})/\Phi(\hat{\gamma}_i' z_{in})$. Adding this second term allows a correlation between the error term in the intensive-margin model and the probability that the stock is held.

   (d) With this new sample of size L_i, estimate the intensive-margin model as in equation (A.13), replacing π_{in} with $\tilde{\pi}_{in}$ and w_{in} with $\tilde{w}_{in}$, and performing the Heckman adjustment. Denote the new intensive-margin model coefficients by $\tilde{b}_{ij}$. Substitute $\tilde{b}_{ij}$ and $\tilde{\pi}_{in}$ into equation (A.11) to obtain $\tilde{w}_{in}^{+}$, also denoted $\tilde{w}^{+}[\mathcal{G}, \tilde{\pi}_i(\mathcal{G})]$. Similarly, compute $\tilde{w}^{+}[\mathcal{G}_0, \tilde{\pi}_i(\mathcal{G}_0)]$.

[25] In 2023, the mean and median of estimated λ_i are -0.258 and -0.270, respectively. Estimated λ_i is negative for more than 95% of institutions and significantly negative at the 5% level for more than 75% of institutions.

(e) Replacing variables with their tilde counterparts, compute $\tilde{\Delta}_{in}$ in equation (1).

(f) Compute $\tilde{T}_i$ from equation (7), substituting $\tilde{\Delta}_{in}$ for Δ_{in}.

5. Repeat step 4 for a total of $NSim$ trials.

6. Compute $TBias_i = \bar{\bar{\tilde{T}}}_i - T_i^{raw}$, where $\bar{\bar{\tilde{T}}}_i$ is the average value of $\tilde{T}_i$ across the $NSim$ trials. $TBias_i$ is the estimated bias in T_i^{raw}.

7. Compute our final bias-adjusted estimate of T_i:

$$\hat{T}_i = T_i^{raw} - TBias_i. \tag{A.16}$$

8. Compute the standard error of $\hat{T}_i$ as follows. Let V_T denote the variance of $\tilde{T}_i$ across the $NSim$ trials. The standard error of $\hat{T}_i$ is $[V_T + V_T/NSim]^{1/2}$. We need to add $V_T/NSim$ because $TBias_i$, an average across $NSim$ trials, is itself estimated with error. The variance of the $TBias_i$ estimate is $V_T/NSim$.

9. We compute a 95% confidence interval for T_i as follows.

(a) The lower end of this interval equals $\hat{T}_i - \text{Gap}_{2.5}$, where $\text{Gap}_{2.5} = \bar{\bar{\tilde{T}}}_i - \tilde{T}_i^{2.5}$ is the gap between the mean and the 2.5th percentile of $\tilde{T}_i$ across simulated trials.

(b) The higher end of this interval equals $\hat{T}_i + \text{Gap}_{97.5}$, where $\text{Gap}_{97.5} = \tilde{T}_i^{97.5} - \bar{\bar{\tilde{T}}}_i$ is the gap between the 97.5th percentile and the mean of $\tilde{T}_i$ across simulated trials.

Online Appendix

Contents:

B.1. Additional data details

The non-ESG stock characteristics, $\mathcal{C}$, are computed as follows. BE/ME is the book-to-market ratio. Book equity equals stockholder equity plus TXDITC (imputing zero if missing) minus BVPS, where stockholder equity equals SEQ if available, otherwise CEQ+PSTK, otherwise AT-LT. BVPS equals PSTKRV if available, otherwise PSTKL, PSTK, or zero. Profitability equals profits divided by end-of-year book equity, where profits equals revenues (REVT) minus COGS minus SG&A (XSGA, imputing zero if missing) minus interest expense (XINT, imputing zero if missing). Profitability is missing if book equity is negative. Investment is the year-over-year fraction change in book assets. These variable definitions follow Fama and French (2015). Dividends/BE is dividends (DVT) divided by end-of-year book equity, replacing DVT with zero if negative. All ratios are from the most recent fiscal year end, and we lag all ratios by six months so investors can observe them. Market cap, computed from CRSP, is observed one month before the beginning of the given time period. We estimate market betas from rolling stock-level time-series regressions of excess stock returns on excess market returns, using the past 60 months of data and requiring at least 24 months of data. Return[-11,-1] is the stock's return during the past 12 months, excluding the most recent one. Note that the most recent month is month zero, i.e., the current month, because holdings are measured at the end of the month.

B.2. Additional estimation details

B.2.1. Estimating the extensive-margin model

This subsection provides additional details supporting Section 3.1, in which we describe the estimation of π_{in}, the probability that investor i holds stock n. We estimate π_{in} from investor-specific probit models. The probit model is a type of regression commonly used to relate a 0/1 dependent variable, denoted Y here, to a vector X of explanatory variables. The probit model assumes

$$\Pr\{Y = 1|X\} = \Phi(X'a), \tag{B.1}$$

where Φ is the cumulative distribution function for the standard normal distribution, and a is a vector of coefficients to be estimated.

We apply the probit model as follows. We set Y equal to $1_{w_{in}>0}$, the indicator for whether investor i holds stock n. Vector $X = X_n$ contains a constant and the characteristics of stock n. In our baseline setting, we use ten characteristics for each stock—three ESG characteristics and seven non-ESG characteristics, where the latter serve as control variables. Vector $a = a_i$ contains investor i's probit coefficients, which describe how each stock characteristic relates to the likelihood that investor i holds a given stock. Using maximum likelihood, we estimate a separate probit model for each investor i, yielding a set of estimated coefficients $\{\hat{a}_i\}$. We then set the estimated probability $\hat{\pi}_{in}$ to $\Phi(X_n'\hat{a}_i)$. We repeat this analysis each quarter.

We find that the probit models fit the data quite well. In our baseline setting applied to data from financial institutions' 13F filings, the average pseudo-R^2 across the institutions' probit models is 0.357 (Section B.2.3). The ten chosen stock-level characteristics go a long way toward explaining which stocks each institution chooses to hold.

Logit is an alternative to probit for modeling 0/1 dependent variables. We choose probit over logit to be consistent with our intensive-margin model. That model includes a Heckman selection correction whose first step involves estimating a probit model with the same dependent variable, an indicator for whether investor i holds stock n (details in Section 3.3 and A.2). We find that our estimates of aggregate ESG tilts are very similar, indeed almost identical, if we switch from probit to logit in the extensive-margin model.

B.2.2. Heckman adjustment

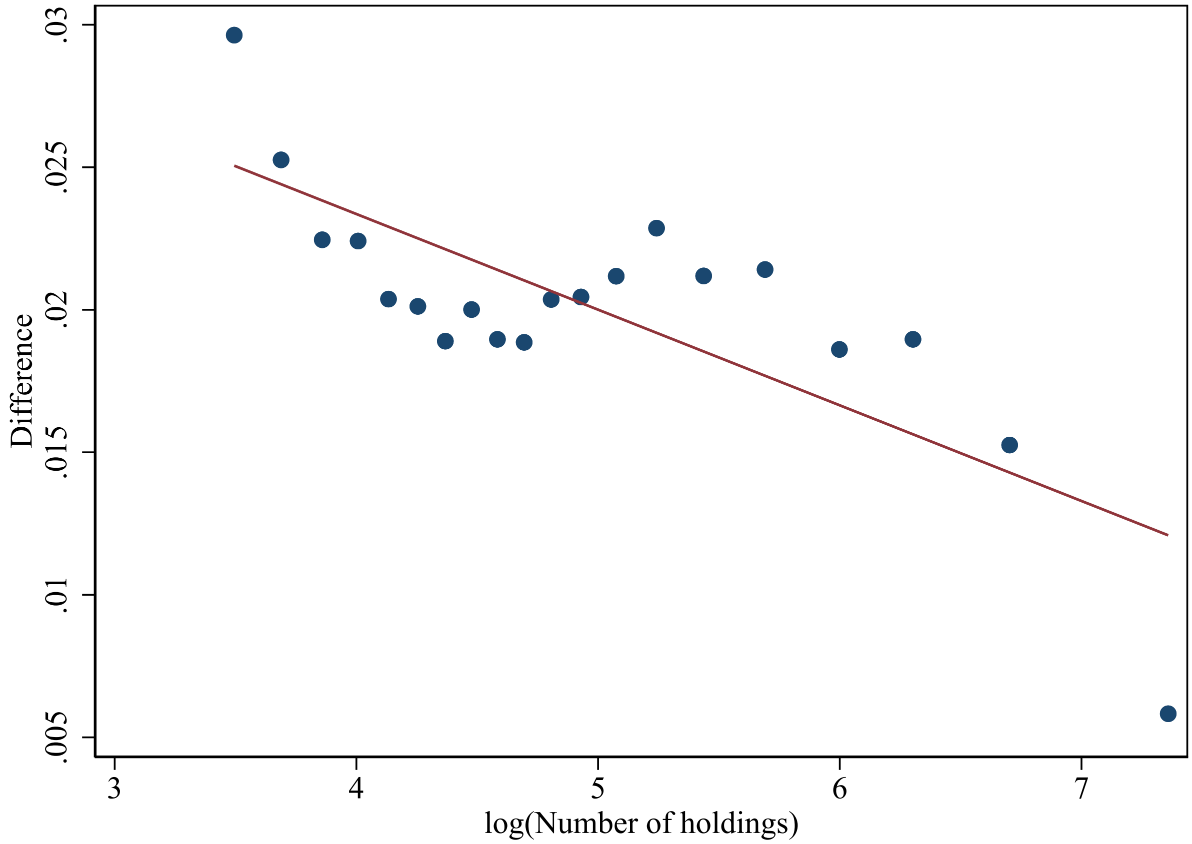


Figure B.1. The effect of the Heckman adjustment and its relation to number of holdings. This is a binscatter plot derived from 13F institutions' estimated tilts from all quarters. The horizontal axis shows the log number of covered stocks held by the institution. The vertical axis shows the absolute value of the difference between two estimates of T_i; one estimate includes a Heckman adjustment and the other does not.

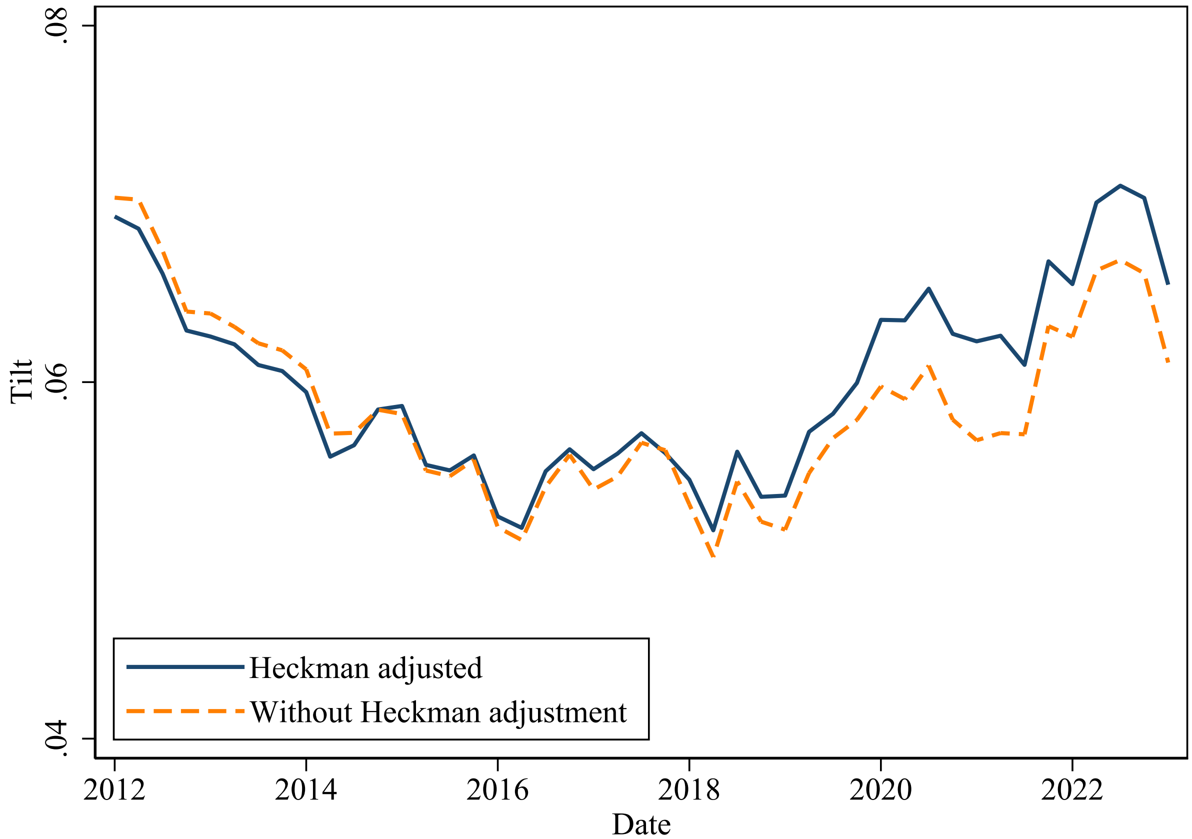


Figure B.2. Aggregate ESG tilts with and without Heckman adjustment. This figure presents the total ESG tilts, both with and without the Heckman adjustment. The Heckman-adjusted tilts are those shown in Figure 1.

B.2.3. Goodness of fit: Extensive and intensive models

Table B.1: Summary statistics on R^2 in the extensive and intensive models

Panel A presents summary statistics on institutions' pseudo R-squared values in the extensive model. Panel B similarly reports summary statistics on R-squared values in the intensive model. Results are from 13F institutions in 2023q4.

Mean	Stdev	p10	p25	Median	p75	p90
Panel A: Extensive model						
0.357	0.146	0.155	0.259	0.367	0.450	0.533
Panel B: Intensive model						
0.414	0.248	0.079	0.202	0.405	0.610	0.760

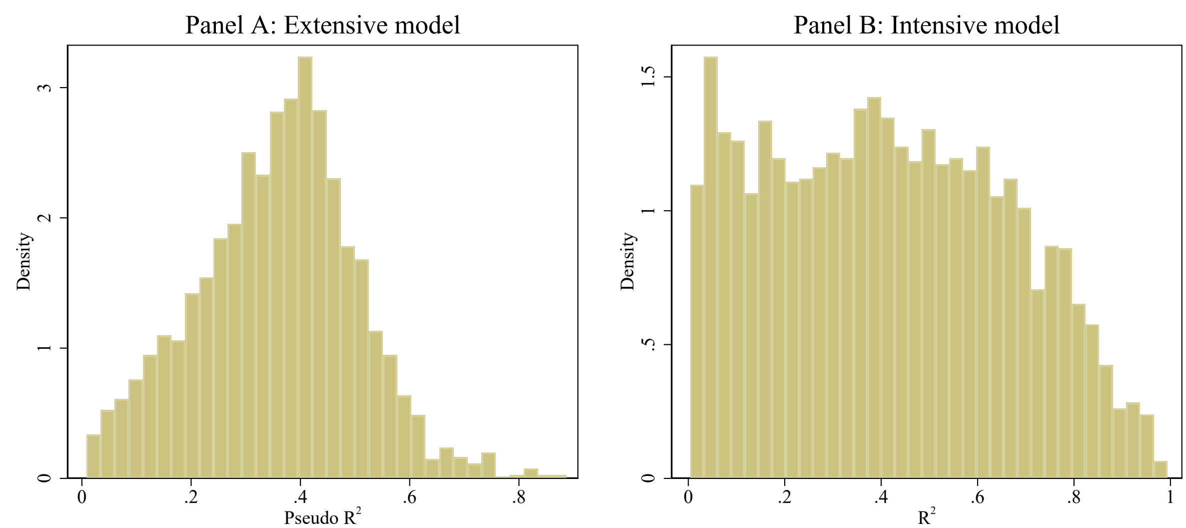


Figure B.3. Histogram of R-squared in extensive and intensive models. Panel A plots the histogram of institutions' pseudo R-squared values in the extensive model. Panel B similarly plots the histogram of R-squared values in the intensive model. Results are from 13F institutions in 2023q4.

B.2.4. Truncation of w_{in}^{+}

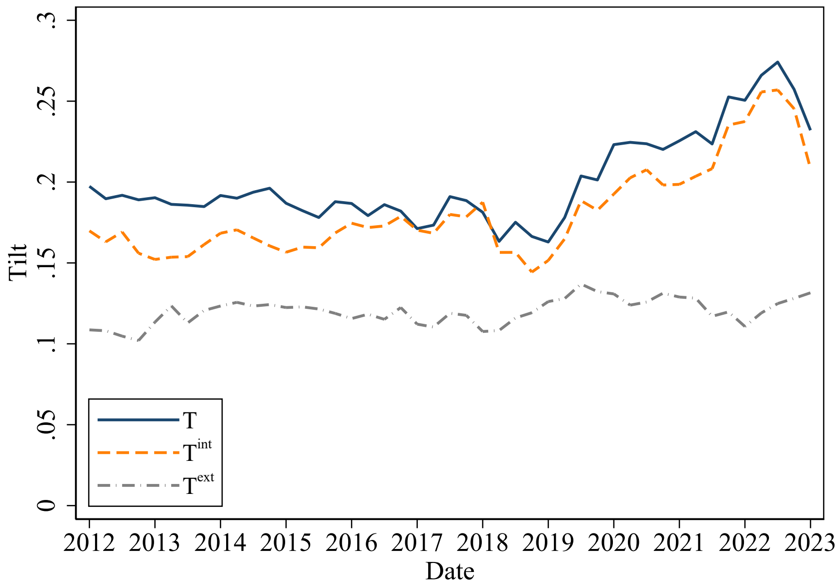
Table B.2: Which institutions or stocks exhibit more truncation?

This table presents results from a regression with dependent variable equal to an indicator for whether w_{in}^{+} is truncated to be in [0,1]. The regression uses 5.8 million institution×stock non-missing observations from 2023q4. Institution types are those used in Table 2, with 1(Insurance) the excluded category. Three AUM size categories are computed using AUM terciles, with the medium category excluded. We use stocks' Fama-French 12 industry classifications and exclude 1(Other). Robust t-statistics double-clustered by institution and stock are in parentheses.

Institution-level dummies:	
1(Inv. advisor)	-0.0051
	(-0.48)
1(Bank)	-0.0205
	(-1.82)
1(Pension/endowment)	-0.0404
	(-3.61)
1(Large AUM)	0.0012
	(0.32)
1(Small AUM)	0.0021
	(0.54)
Stock-level dummies:	
1(NoDur)	0.0086
	(0.65)
1(Durbl)	-0.0074
	(-0.58)
1(Manuf)	-0.0154
	(-2.25)
1(Enrgy)	0.0207
	(1.57)
1(Chems)	-0.0079
	(-0.86)
1(BusEq)	-0.0005
	(-0.07)
1(Telcm)	0.0173
	(0.91)
1(Utils)	0.0212
	(1.84)
1(Shps)	-0.0155
	(-2.00)
1(Hlth)	-0.0119
	(-1.87)
1(Money)	-0.0075
	(-1.13)
R^2	0.003

B.3. Additional results on 13F institutions' tilts, without industry adjustment

Panel A: Institutions holding a below-median number of stocks



Panel B: Institutions holding an above-median number of stocks

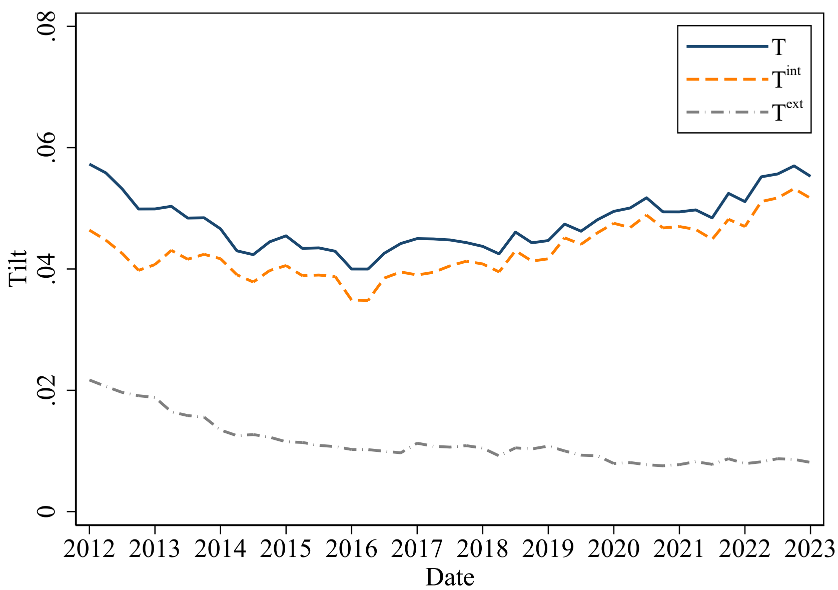


Figure B.4. ESG-related tilts in subsamples based on number of stocks held. Tilts in this figure are the same as in the paper's Figure 1 Panel A, except we show tilts aggregated within two subsamples. In each quarter, we calculate the median number of stocks held across institutions, and we split the institutions in two groups based on whether their number of stocks held is below the median (Panel A) or at or above the median (Panel B). The median number of holdings ranges from 104 to 121 across quarters.

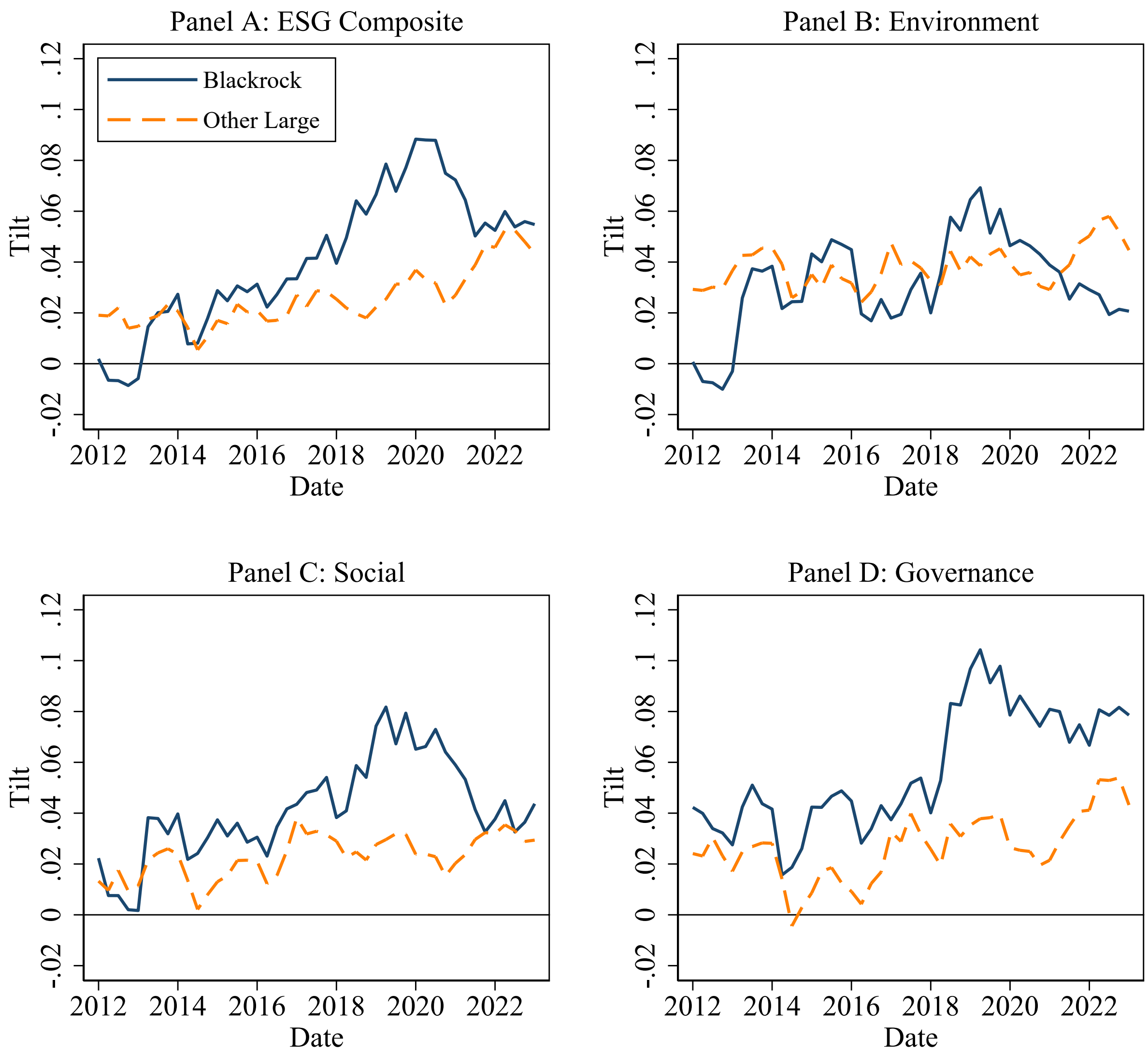


Figure B.5. GMB tilts of BlackRock and other large institutions. This figure compares Blackrock's GMB tilt to the AUM-weighted average GMB tilt of other large institutions. The lines labeled "Large" in Figure 6 are AUM-weighted averages of the two lines in each panel of this figure.

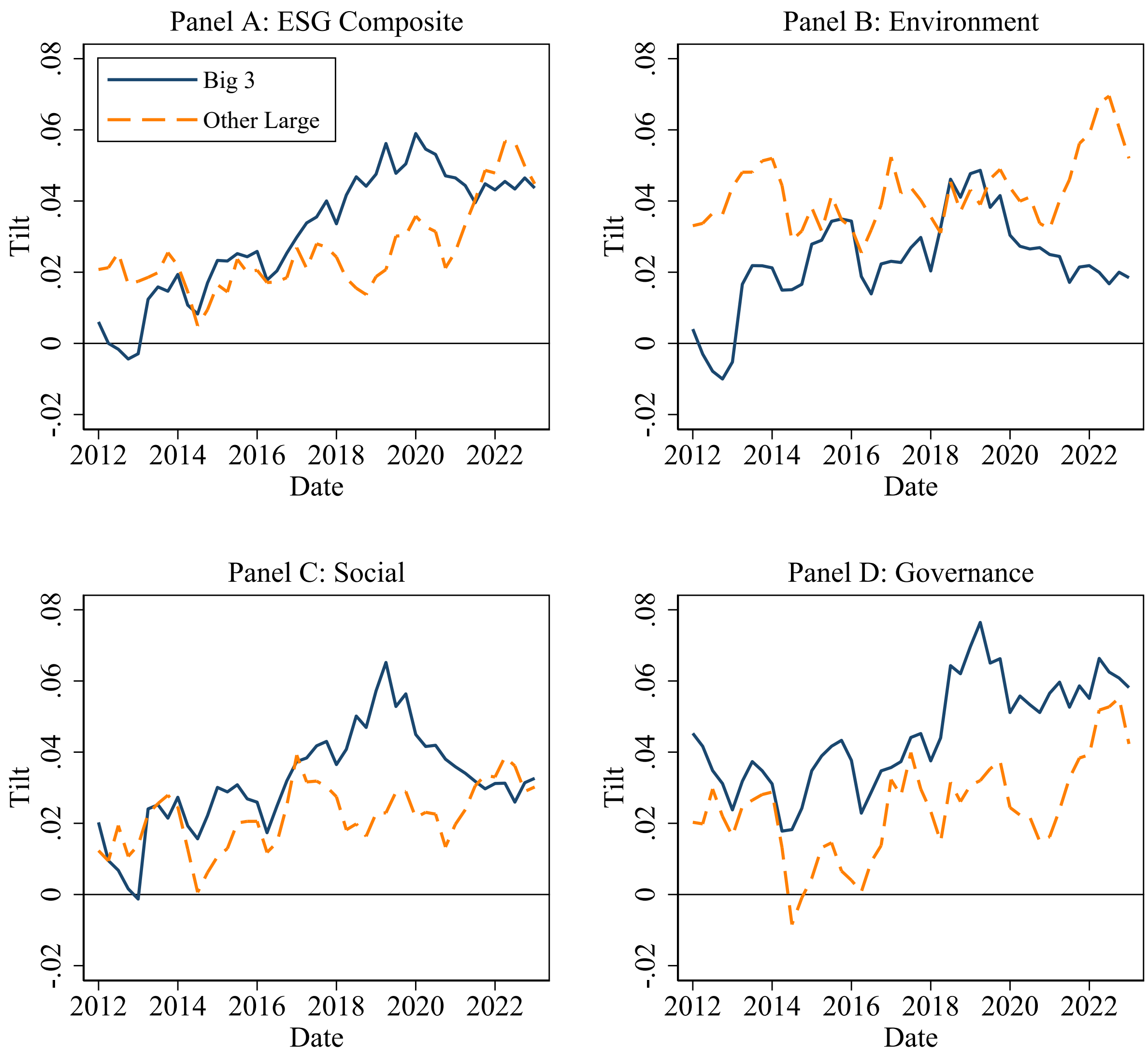
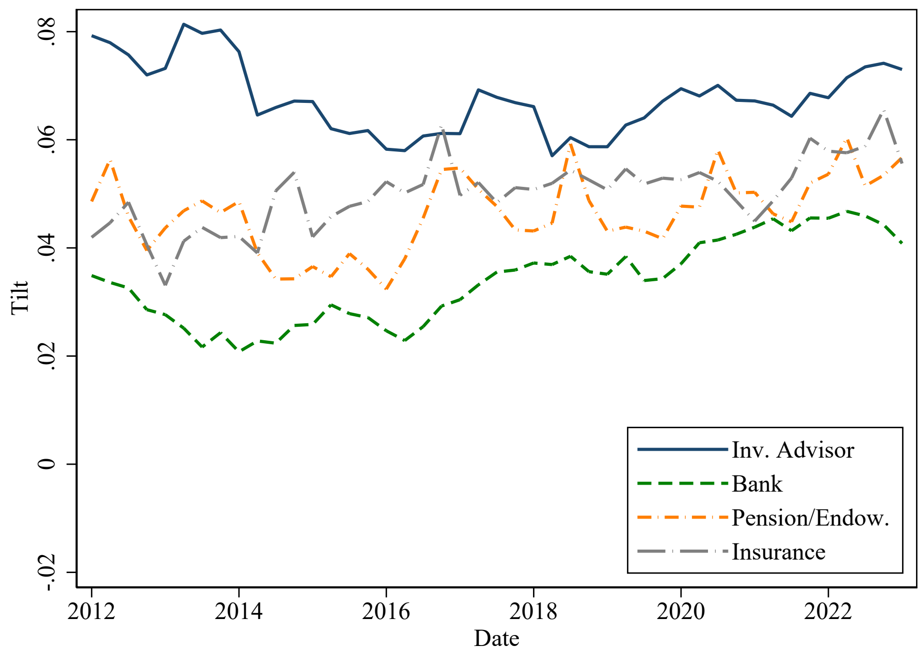


Figure B.6. GMB tilts of the Big Three and other large institutions. This figure compares GMB tilts between the subsample of Big Three institutions and other large institutions. Each line shows the AUM-weighted average of GMB tilt within the given subsample of institutions. The lines labeled "Large" in Figure 6 of the paper are AUM-weighted averages of the two lines in each panel of this figure.

Panel A: ESG tilts



Panel B: GMB tilts

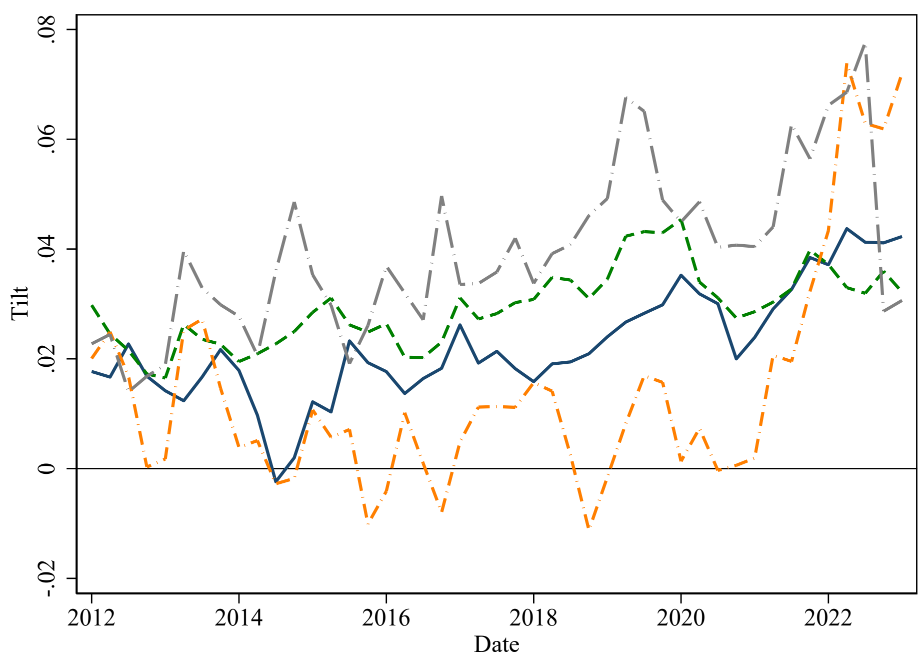


Figure B.7. Comparing tilts across institution types. Panel A (B) plots the AUM-weighted average of T_i (T_i^{GMB}). GMB tilts are computed using the ESG composite score to measure greenness.

Table B.3: Version of paper's Table 2 with time and institution fixed effects

This table shows results from panel regressions with dependent variable equal to GMB tilt and both time and institution fixed effects. Including these fixed effects requires dropping Trend, institution-type indicators, and indicators for geographical location from the regression. Remaining details are the same as in Table 2.

	ESG	Env.	Soc.	Gov.
log(AUM)	0.0075	-0.0158	0.0103	-0.0018
	(1.29)	(-2.24)	(1.43)	(-0.29)
log(AUM) x trend	0.0688	0.0409	0.0509	0.0090
	(6.27)	(3.44)	(4.12)	(0.84)
Active share	-0.0110	-0.0551	0.0352	-0.0428
	(-0.26)	(-1.07)	(0.68)	(-0.99)
1(UNPRI)	0.0249	0.0454	0.0174	-0.0042
	(1.67)	(2.60)	(1.11)	(-0.29)
R^2	0.439	0.448	0.499	0.409
R^2 (FEs only)	0.436	0.447	0.498	0.409

Table B.4: Version of paper's Table 3 with time fixed effects

This table is the same as Table 3 but includes time fixed effects, which requires dropping Trend from the regression.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0036	-0.0015	0.0043	0.0038	-0.0195	-0.0071	-0.0208	-0.0156
	(2.56)	(-0.75)	(2.46)	(3.04)	(-11.05)	(-4.40)	(-9.68)	(-8.75)
log(AUM) × trend	0.0288	0.0310	0.0188	0.0028	-0.0516	-0.0178	-0.0363	-0.0071
	(5.33)	(4.23)	(2.98)	(0.61)	(-8.93)	(-3.04)	(-5.32)	(-1.12)
Active share	0.0900	0.1440	0.1284	0.0949	0.0916	0.1553	0.1153	0.1408
	(9.95)	(11.04)	(11.38)	(10.53)	(8.50)	(13.34)	(7.82)	(11.29)
1(UNPRI)	0.0223	0.0215	0.0117	0.0020	-0.0230	-0.0223	-0.0351	-0.0159
	(3.63)	(2.82)	(1.73)	(0.43)	(-4.22)	(-4.19)	(-5.48)	(-2.79)
1(Inv. advisor)	-0.0030	0.0064	0.0048	-0.0165	0.0216	0.0044	0.0106	0.0048
	(-0.33)	(0.43)	(0.48)	(-1.60)	(2.81)	(0.52)	(0.60)	(0.31)
1(Bank)	-0.0172	-0.0121	-0.0304	-0.0299	0.0685	0.0170	0.1096	0.0324
	(-1.73)	(-0.77)	(-2.71)	(-2.60)	(5.17)	(1.56)	(4.45)	(1.78)
1(Pension/endowment)	-0.0055	-0.0077	0.0104	-0.0053	0.0074	0.0057	-0.0106	-0.0112
	(-0.57)	(-0.47)	(0.86)	(-0.44)	(0.74)	(0.47)	(-0.57)	(-0.64)
1(Europe)	0.0279	0.0393	0.0284	0.0270	-0.0070	-0.0117	-0.0237	-0.0116
	(2.93)	(3.59)	(2.64)	(3.55)	(-0.94)	(-1.49)	(-2.74)	(-1.45)
1(Rest of world)	0.0107	0.0267	0.0158	0.0139	-0.0011	-0.0129	-0.0076	0.0011
	(1.20)	(2.27)	(1.46)	(1.57)	(-0.13)	(-1.48)	(-0.70)	(0.10)
R^2	0.021	0.026	0.025	0.016	0.044	0.032	0.044	0.042
R^2 (FEs only)	0.004	0.002	0.002	0.002	0.016	0.002	0.007	0.004
p (Inst. types equal)	0.081	0.060	0.000	0.012	0.000	0.392	0.000	0.014

Table B.5: Version of paper's Table 3 with institution and time fixed effects

This table is the same as Table 3 but includes institution and time fixed effects, which requires dropping Trend, institution-type indicators, and indicators for geographical location from the regression.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	-0.0013	-0.0113	0.0029	-0.0017	-0.0110	0.0029	-0.0109	-0.0008
	(-0.42)	(-2.56)	(0.74)	(-0.54)	(-3.05)	(0.81)	(-2.42)	(-0.21)
log(AUM) $\times$ trend	0.0216	0.0288	0.0169	0.0030	-0.0497	-0.0136	-0.0363	-0.0057
	(3.64)	(3.81)	(2.49)	(0.57)	(-7.57)	(-2.16)	(-4.88)	(-0.84)
Active share	0.1045	0.1157	0.1472	0.0905	0.1124	0.1610	0.1034	0.1240
	(4.65)	(3.81)	(5.37)	(4.14)	(4.02)	(5.61)	(3.10)	(4.42)
1(UNPRI)	0.0126	0.0247	-0.0005	-0.0014	-0.0125	-0.0204	-0.0175	0.0028
	(1.42)	(2.05)	(-0.05)	(-0.19)	(-1.45)	(-2.30)	(-1.94)	(0.29)
R^2	0.378	0.435	0.427	0.342	0.441	0.434	0.504	0.421
R^2 (FEs only)	0.38	0.435	0.427	0.346	0.441	0.434	0.507	0.423

Table B.6
Additional details on aggregate tilts

Panel A: T

Year	Bias-Adj. Estimate	Standard Error	95% CI Low	95% CI High	Bias
2012	0.069	0.002	0.066	0.073	0.010
2013	0.063	0.002	0.059	0.066	0.011
2014	0.059	0.002	0.056	0.063	0.011
2015	0.059	0.002	0.055	0.062	0.010
2016	0.052	0.002	0.049	0.056	0.010
2017	0.055	0.002	0.052	0.059	0.009
2018	0.055	0.002	0.051	0.058	0.008
2019	0.054	0.002	0.050	0.057	0.009
2020	0.063	0.002	0.060	0.067	0.002
2021	0.062	0.001	0.059	0.065	0.002
2022	0.065	0.002	0.062	0.069	0.002
2023	0.065	0.001	0.063	0.068	0.001

Panel B: T^{int}

Year	Bias-Adj. Estimate	Standard Error	95% CI Low	95% CI High	Bias
2012	0.057	0.002	0.054	0.060	0.010
2013	0.051	0.002	0.048	0.054	0.011
2014	0.053	0.002	0.050	0.056	0.010
2015	0.051	0.002	0.048	0.054	0.009
2016	0.047	0.002	0.044	0.050	0.009
2017	0.050	0.002	0.046	0.053	0.008
2018	0.052	0.002	0.049	0.055	0.006
2019	0.050	0.001	0.047	0.053	0.007
2020	0.059	0.002	0.056	0.062	0.001
2021	0.058	0.001	0.056	0.061	0.001
2022	0.061	0.002	0.057	0.064	0.002
2023	0.061	0.001	0.058	0.063	0.000

Panel C: T^{ext}

Year	Bias-Adj. Estimate	Standard Error	95% CI Low	95% CI High	Bias
2012	0.029	0.001	0.027	0.031	0.005
2013	0.027	0.001	0.026	0.029	0.005
2014	0.023	0.001	0.021	0.025	0.005
2015	0.022	0.001	0.020	0.024	0.004
2016	0.019	0.001	0.018	0.021	0.004
2017	0.019	0.001	0.017	0.021	0.004
2018	0.018	0.001	0.016	0.020	0.004
2019	0.020	0.001	0.018	0.021	0.004
2020	0.018	0.001	0.016	0.020	0.003
2021	0.017	0.001	0.015	0.018	0.003
2022	0.015	0.001	0.014	0.017	0.003
2023	0.015	0.000	0.014	0.016	0.002

B.4. Additional results on 13F institutions' industry-adjusted tilts

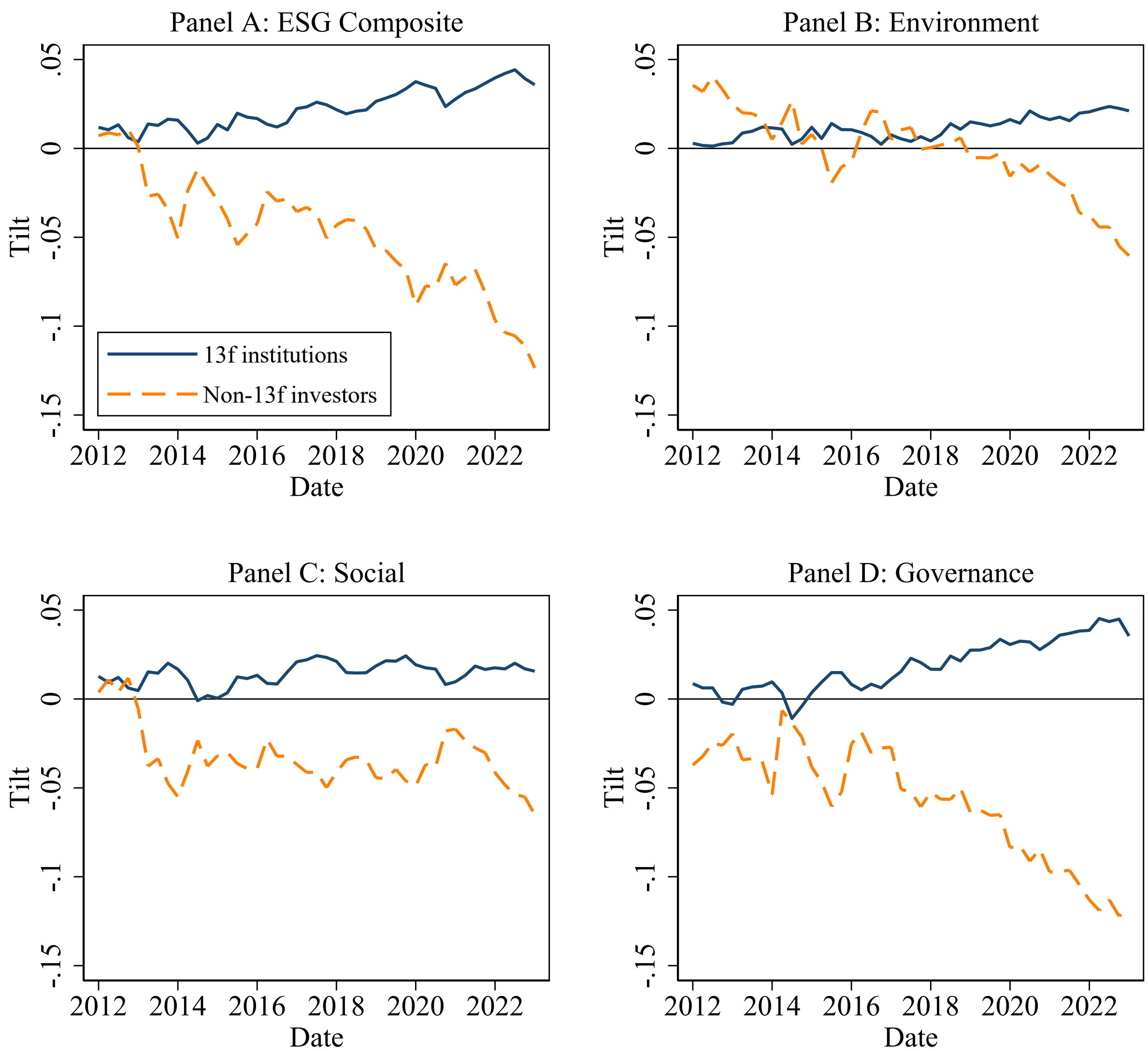


Figure B.8. Industry-adjusted GMB tilts of 13F filers and non-filers. This figure plots the same quantities as in Figure 4 but uses industry-adjusted ESG scores. Additional details are in Figure 7.

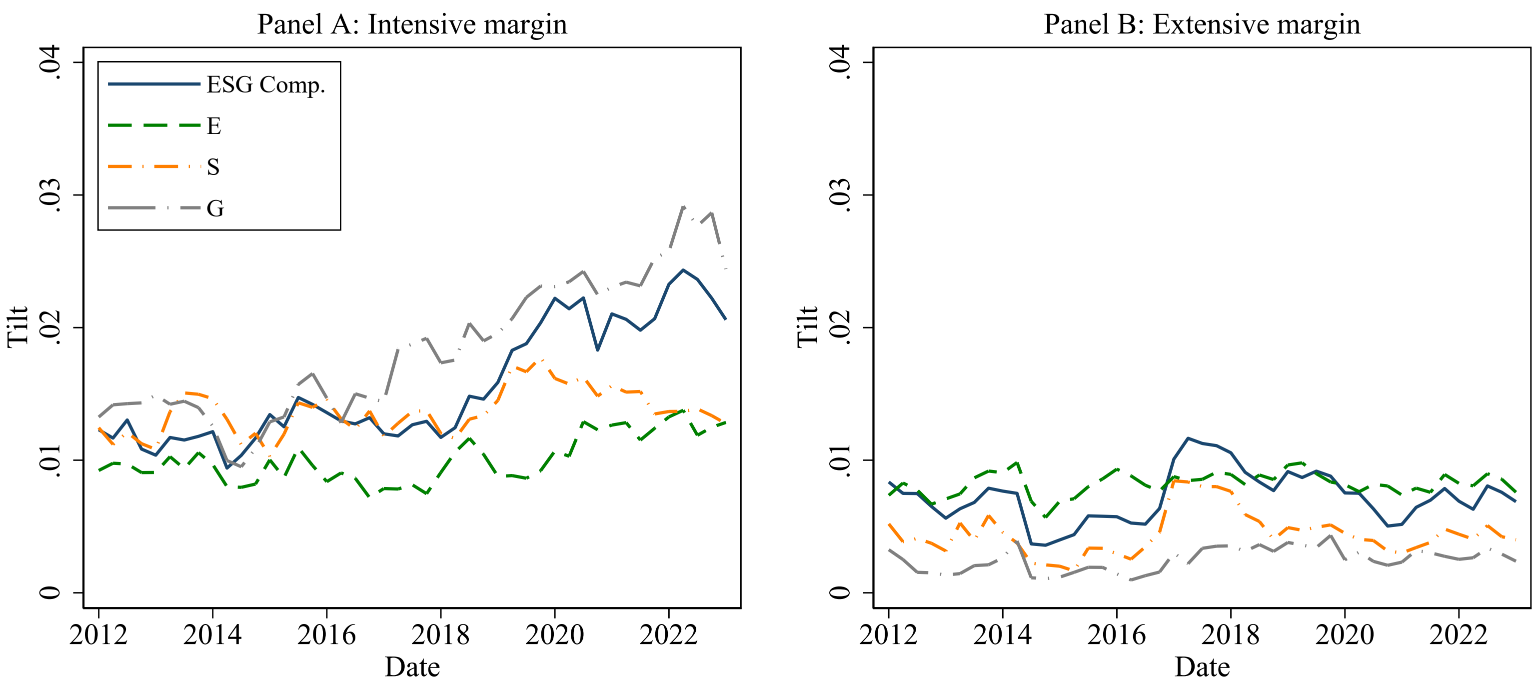


Figure B.9. Divestment from brown stocks, with industry adjustment. This figure plots the same quantities as in Figure 5 but uses industry-adjusted ESG scores. Additional details are in Figure 7.

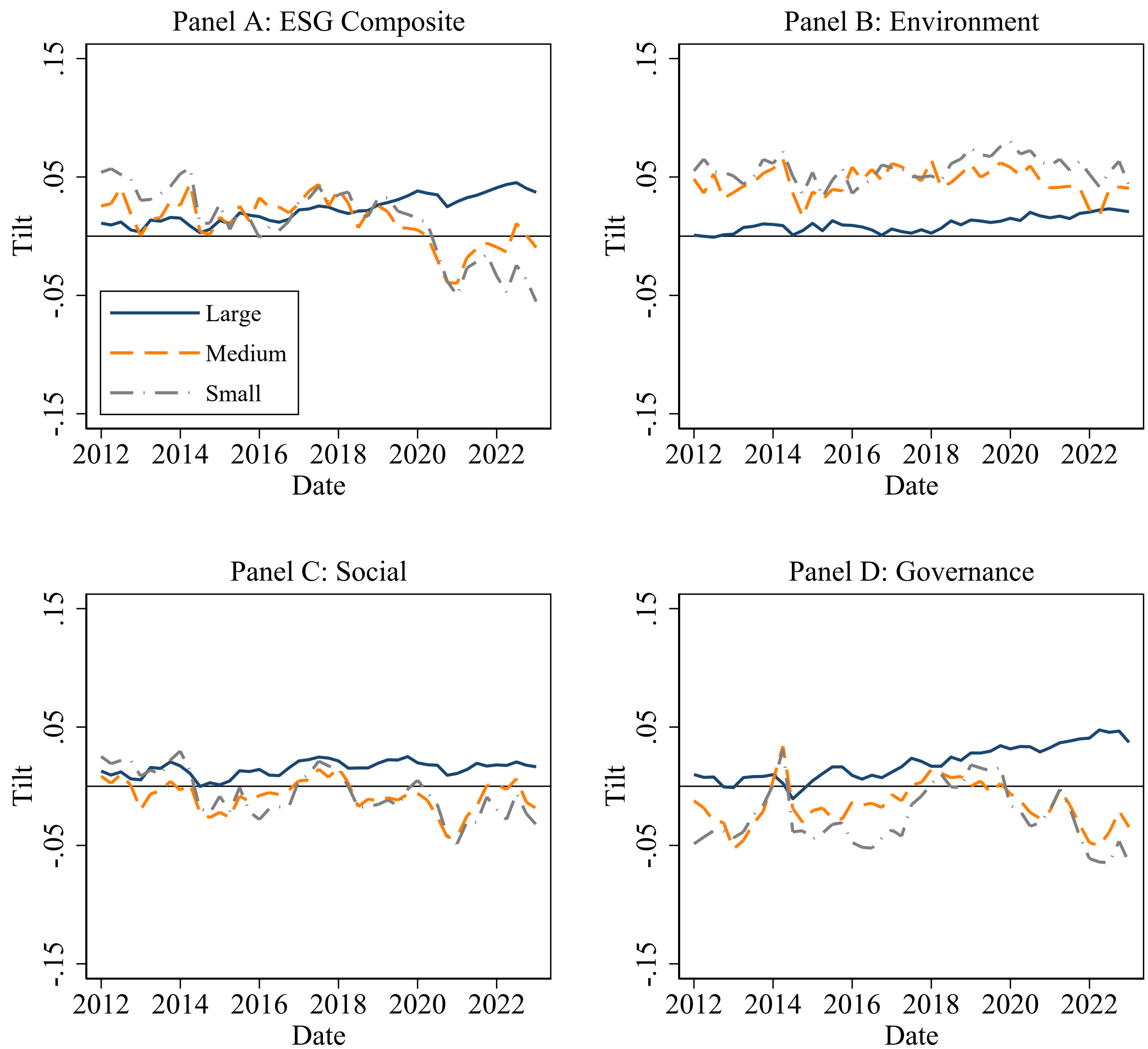


Figure B.10. Institution size and greenness, with industry adjustments. This figure plots the same quantities as Figure 6 but uses industry-adjusted ESG scores. Additional details are in Figure 7.

Table B.7
Aggregate industry-adjusted tilts

This table shows the same quantities as in Table 1 but uses industry-adjusted ESG scores. Additional details are in Figure 7.

	Estimated Tilt			Standard Error		
Year	Total	Intensive	Extensive	Total	Intensive	Extensive
2012	0.047	0.039	0.017	0.002	0.001	0.001
2013	0.051	0.043	0.017	0.002	0.002	0.001
2014	0.047	0.040	0.015	0.001	0.001	0.001
2015	0.042	0.036	0.013	0.001	0.001	0.001
2016	0.043	0.040	0.013	0.001	0.001	0.001
2017	0.046	0.039	0.014	0.002	0.002	0.001
2018	0.050	0.045	0.014	0.002	0.002	0.001
2019	0.047	0.043	0.012	0.002	0.001	0.001
2020	0.050	0.048	0.011	0.001	0.002	0.001
2021	0.054	0.051	0.011	0.001	0.001	0.001
2022	0.051	0.049	0.011	0.001	0.001	0.001
2023	0.051	0.047	0.010	0.001	0.001	0.000

Table B.8: Which institutions are greener?
Version with industry-adjusted ESG scores

This table shows the same quantities as in Table 2 but uses industry-adjusted ESG scores. Additional details are in Figure 7.

	No Fixed Effects				Time Fixed Effects				Institution Fixed Effects			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0099	-0.0078	0.0059	0.0093	0.0087	-0.0079	0.0054	0.0078	-0.0042	-0.0195	0.0005	-0.0034
	(4.40)	(-3.43)	(2.74)	(4.23)	(3.87)	(-3.50)	(2.49)	(3.53)	(-0.77)	(-3.68)	(0.09)	(-0.69)
log(AUM) $\times$ trend	0.0553	0.0133	0.0217	0.0226	0.0502	0.0119	0.0198	0.0145	0.0452	0.0122	0.0236	0.0190
	(6.55)	(1.71)	(2.75)	(2.90)	(5.96)	(1.54)	(2.50)	(1.85)	(4.73)	(1.38)	(2.65)	(2.14)
Trend	0.4693	0.1238	0.1676	0.2531					0.3707	0.0899	0.2023	0.2357
	(5.51)	(1.59)	(2.10)	(3.19)					(4.03)	(1.05)	(2.36)	(2.75)
Active share	-0.0258	-0.0288	-0.0246	-0.0321	-0.0246	-0.0276	-0.0244	-0.0294	-0.0373	-0.0942	0.0193	-0.0118
	(-1.78)	(-2.08)	(-1.75)	(-2.18)	(-1.69)	(-1.98)	(-1.73)	(-1.99)	(-0.99)	(-2.43)	(0.56)	(-0.34)
1(UNPRI)	0.0315	0.0143	0.0230	0.0178	0.0325	0.0143	0.0235	0.0186	0.0225	0.0194	0.0066	-0.0034
	(3.85)	(1.77)	(3.09)	(2.43)	(3.98)	(1.76)	(3.17)	(2.55)	(1.80)	(1.51)	(0.53)	(-0.28)
1(Inv. advisor)	-0.0239	-0.0073	-0.0039	-0.0135	-0.0243	-0.0074	-0.0041	-0.0140				
	(-1.62)	(-0.45)	(-0.29)	(-0.69)	(-1.65)	(-0.46)	(-0.31)	(-0.71)				
1(Bank)	-0.0287	-0.0247	-0.0477	0.0267	-0.0290	-0.0247	-0.0480	0.0266				
	(-1.55)	(-1.41)	(-2.79)	(1.18)	(-1.57)	(-1.41)	(-2.81)	(1.17)				
1(Pension/endowment)	-0.0217	-0.0231	-0.0044	-0.0024	-0.0216	-0.0229	-0.0044	-0.0021				
	(-1.33)	(-1.32)	(-0.30)	(-0.11)	(-1.32)	(-1.31)	(-0.29)	(-0.10)				
1(Europe)	0.0146	0.0301	0.0032	-0.0002	0.0139	0.0298	0.0030	-0.0014				
	(1.26)	(2.55)	(0.30)	(-0.02)	(1.19)	(2.52)	(0.28)	(-0.14)				
1(Rest of world)	-0.0073	0.0156	-0.0177	-0.0336	-0.0081	0.0155	-0.0178	-0.0349				
	(-0.60)	(1.30)	(-1.44)	(-2.63)	(-0.67)	(1.28)	(-1.46)	(-2.72)				
R^2	0.006	0.005	0.004	0.006	0.009	0.006	0.006	0.010	0.406	0.418	0.411	0.374
R^2 (FEs only)	N/A	N/A	N/A	N/A	0.005	0.001	0.003	0.004	0.403	0.417	0.410	0.374
p (Inst. types equal)	0.400	0.102	0.003	0.022	0.384	0.109	0.003	0.020	N/A	N/A	N/A	N/A

Table B.9: Green and brown tilts
Version with industry-adjusted ESG scores

This table shows the same quantities as in Table 3 but uses industry-adjusted ESG scores. Additional details are in Figure 7.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	-0.0012	-0.0109	-0.0036	0.0003	-0.0111	-0.0031	-0.0095	-0.0089
	(-0.98)	(-7.43)	(-3.07)	(0.29)	(-7.89)	(-2.60)	(-7.01)	(-6.49)
log(AUM) $\times$ trend	0.0292	0.0066	0.0068	0.0189	-0.0260	-0.0067	-0.0148	-0.0038
	(5.93)	(1.34)	(1.51)	(4.64)	(-5.36)	(-1.59)	(-3.17)	(-0.76)
Trend	0.2900	0.1089	0.0867	0.2135	-0.1793	-0.0150	-0.0809	-0.0395
	(5.83)	(2.18)	(1.89)	(5.15)	(-3.67)	(-0.35)	(-1.71)	(-0.79)
Active share	0.0702	0.0807	0.0674	0.0680	0.0961	0.1096	0.0920	0.1001
	(8.51)	(8.96)	(9.09)	(8.55)	(10.66)	(15.19)	(10.30)	(10.90)
1(UNPRI)	0.0146	0.0063	0.0053	0.0058	-0.0169	-0.0080	-0.0177	-0.0120
	(2.79)	(1.18)	(1.18)	(1.43)	(-3.79)	(-1.98)	(-4.18)	(-2.63)
1(Inv. advisor)	-0.0086	-0.0025	0.0039	-0.0126	0.0153	0.0047	0.0078	0.0009
	(-0.88)	(-0.21)	(0.48)	(-1.08)	(2.02)	(0.75)	(1.04)	(0.09)
1(Bank)	0.0025	-0.0137	-0.0152	0.0253	0.0312	0.0110	0.0326	-0.0014
	(0.22)	(-1.09)	(-1.69)	(1.83)	(2.90)	(1.46)	(2.98)	(-0.11)
1(Pension/endowment)	-0.0157	-0.0147	-0.0067	-0.0139	0.0060	0.0084	-0.0022	-0.0115
	(-1.48)	(-1.15)	(-0.74)	(-1.17)	(0.67)	(1.11)	(-0.25)	(-0.95)
1(Europe)	0.0096	0.0239	-0.0014	0.0002	-0.0050	-0.0063	-0.0045	0.0004
	(1.21)	(2.99)	(-0.22)	(0.04)	(-0.85)	(-1.07)	(-0.74)	(0.07)
1(Rest of world)	-0.0073	0.0067	-0.0101	-0.0227	0.0000	-0.0089	0.0076	0.0110
	(-1.05)	(0.82)	(-1.68)	(-3.94)	(0.01)	(-1.50)	(0.95)	(1.25)
R^2	0.016	0.031	0.016	0.014	0.028	0.025	0.026	0.027
p (Inst. types equal)	0.110	0.078	0.001	0.000	0.010	0.441	0.003	0.391

B.5. Results using Sustainalytics scores

B.5.1. Data and summary statistics

Similar to MSCI, Sustainalytics measures ESG risk performance at the company level. In 2018, Sustainalytics made a major change to its ESG ratings methodology. Prior to this shift, the data reflected aggregated ESG performance scores based on the underlying E, S, and G pillars, with scores ranging from 0 to 100, where higher scores indicated stronger ESG performance. In contrast, the updated ESG Risk Ratings introduced in 2018 measure ESG risk aggregating scores from material ESG issues, with higher scores (also from 0 to 100) signifying greater risk, which is considered negative. WRDS has recently removed the legacy Sustainalytics data and now encourages users to fully transition to the updated ESG Risk Ratings.[26] We begin our Sustainalytics analysis in 2018 so that we use the updated methodology and avoid mixing methodologies.

Sustainalytics calculates its ESG Risk Score by summing the ESG Risk Score across Material ESG Issues (MEIs). For each MEI, the ESG Risk Score is further divided into an Exposure Score (ES) and a Managed Risk Score (MRS). Formally, for each firm i and each pillar $n \in \{E, S, G\}$, Sustainalytics defines the firm's Exposure and Managed Risk Scores on the pillar as

$$ES_{i,n,t} = \sum_{j \in S} \omega_{j,n,t} MEI\_ES_{i,j,t} \tag{B.2}$$

$$MRS_{i,n,t} = \sum_{j \in S} \omega_{j,n,t} MEI\_MRS_{i,j,t}, \tag{B.3}$$

where $S = \{MEI_1, MEI_2, \ldots, MEI_j, \ldots, MEI_{55}\}$ and $\omega_{j,n,t}$ is MEI j's weight in the risk score at time t for pillar n.[27] Then, the firm's E, S, G, and overall ESG Risk Score are defined as

$$ER_{i,n,t} = ES_{i,n,t} - MRS_{i,n,t} \tag{B.4}$$

$$ER_{i,t} = \sum_{n \in \{E,S,G\}} (ES_{i,n,t} - MRS_{i,n,t}). \tag{B.5}$$

There is a parallel between the MSCI and Sustainalytics scores: just as the E, S, and G measures we use from MSCI sum to WAKI (plus a constant), the E, S, and G measures we use from Sustainalytics sum to $ER_{i,t}$. Similar to MSCI's data, $ER_{i,t}$ is explicitly not industry

[26] As described by WRDS, "the legacy Sustainalytics measures ESG performance rather than ESG risk. In 2018, Sustainalytics decided to retire the legacy method and database as they launched a new product, Sustainalytics ESG Risk Ratings. Therefore, ESG Risk Ratings cannot be an extension of the legacy Sustainalytics."

[27] Note that a single MEI can be tied to multiple ESG pillars. Sustainalytics applies two layers of weighting: 1) MEI weights that determine the contribution of each MEI to the overall risk score, and 2) E, S, and G weights allocated within each MEI. We combine these two weight structures into a single weight $\omega_{j,n,t}$.

adjusted. We multiply the Sustainalytics ratings by -1 to align with MSCI's scoring, such that higher scores reflect a greener firm. We calculate the cross-sectional percentile for each variable in Sustainalytics, as we do with the MSCI scores.

We obtain from WRDS the Sustainalytics overall ESG Risk Score ($ER_{i,t}$) and E, S, and G cluster score ($ER_{i,n,t}$), starting from December 2018. The cluster scores are often missing, even when the overall ESG score is non-missing.

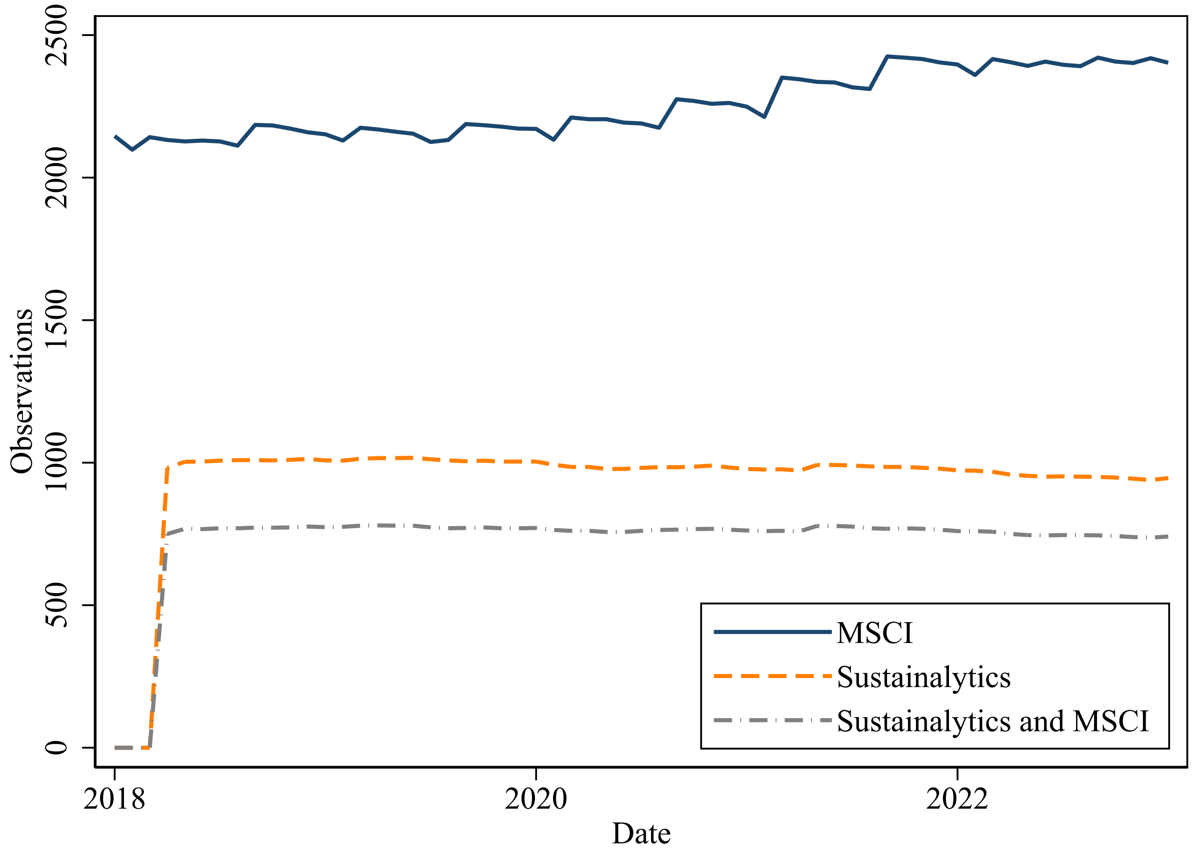


Figure B.11. MSCI and Sustainalytics coverage. This figure shows the number of firms with MSCI and Sustainalytics coverage. "MSCI" denotes firms with non-missing E, S, G, and composite ESG ratings in MSCI. Similarly, "Sustainalytics" denotes firms with complete ratings for the E, S, and G pillars in Sustainalytics. "Sustainalytics and MSCI" denotes firms with complete Sustainalytics and MSCI ratings. This figure does not require non-missing CRSP/Compustat data.

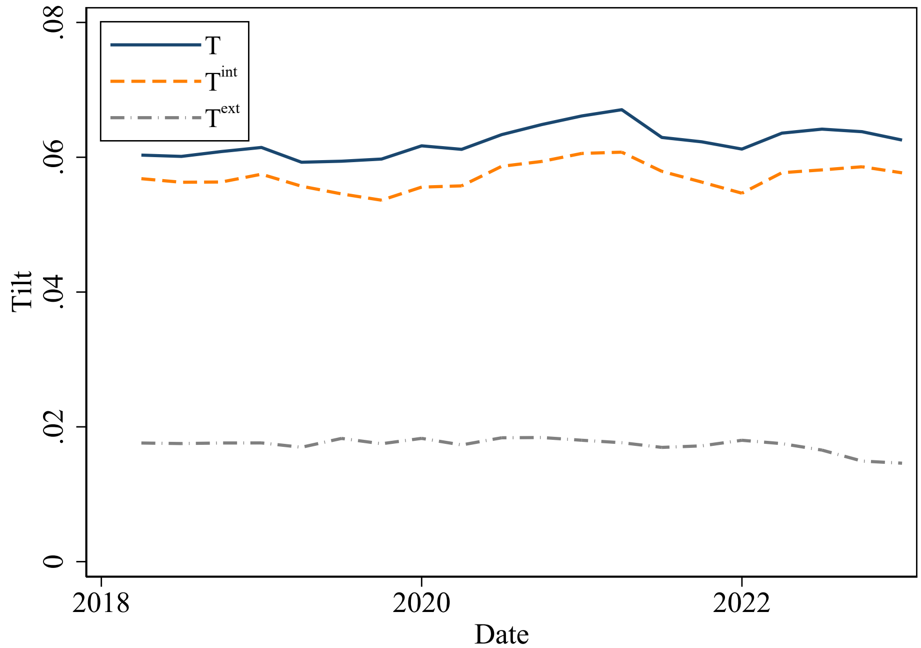
Table B.10. Correlation between MSCI and Sustainalytics Ratings

This table shows the correlation between MSCI and Sustainalytics ESG ratings. Both MSCI and Sustainalytics scores are adjusted by subtracting their respective market means within each quarter. We multiply Sustainalytics scores by -1. The first column reports the correlation between MSCI ratings and the Sustainalytics ESG ratings. The second column shows the correlation based on cross-sectional percentiles of MSCI and Sustainalytics ratings.

	Level	Percentile
Composite ESG Score	0.27	0.25
E Score	0.78	0.68
S Score	0.19	0.21
G Score	0.17	0.24

B.5.2. Tilts estimated using Sustainalytics scores

Panel A: Raw tilts



Panel B: Tilts divided by active share

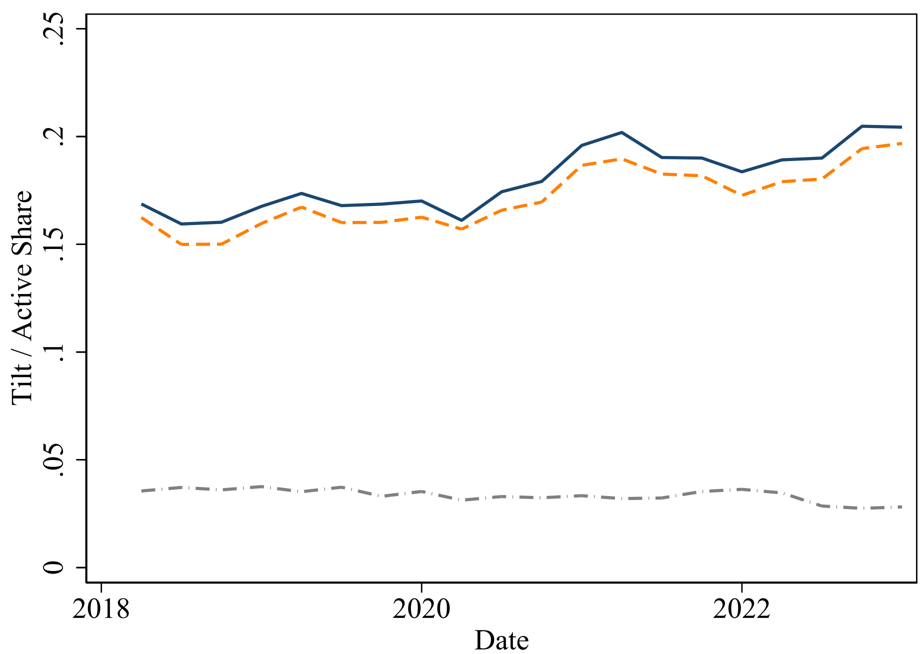


Figure B.12. Total, intensive, and extensive ESG tilts (version with Sustainalytics scores). This figure plots the same quantities as in Figure 1 but with Sustainalytics data.

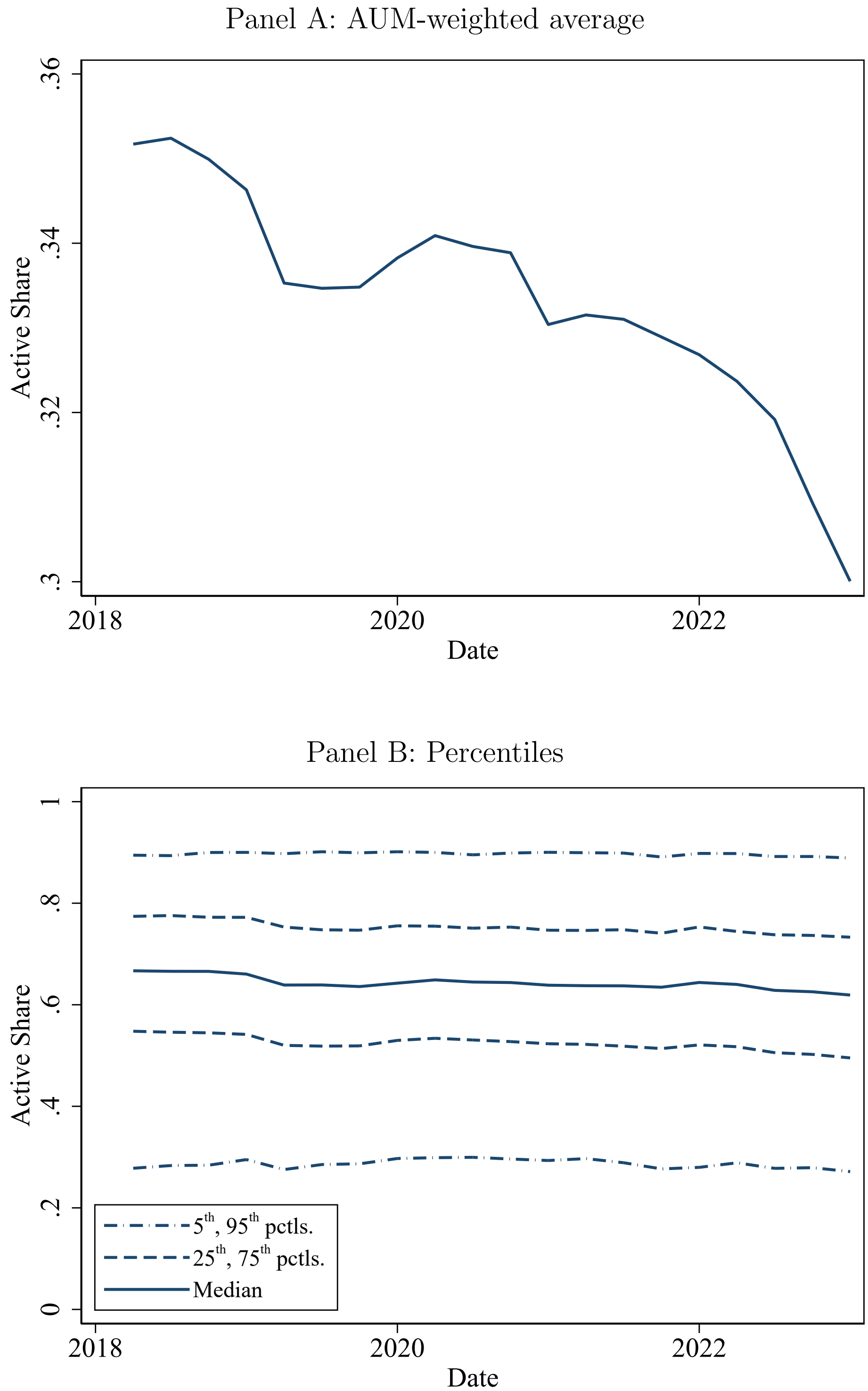


Figure B.13. Active share (version with Sustainalytics scores). This figure plots the same quantities as in Figure 2 but with Sustainalytics data. The figure differs from its MSCI version because the universe of covered stocks is different, and each analysis studies only the holdings of covered stocks.

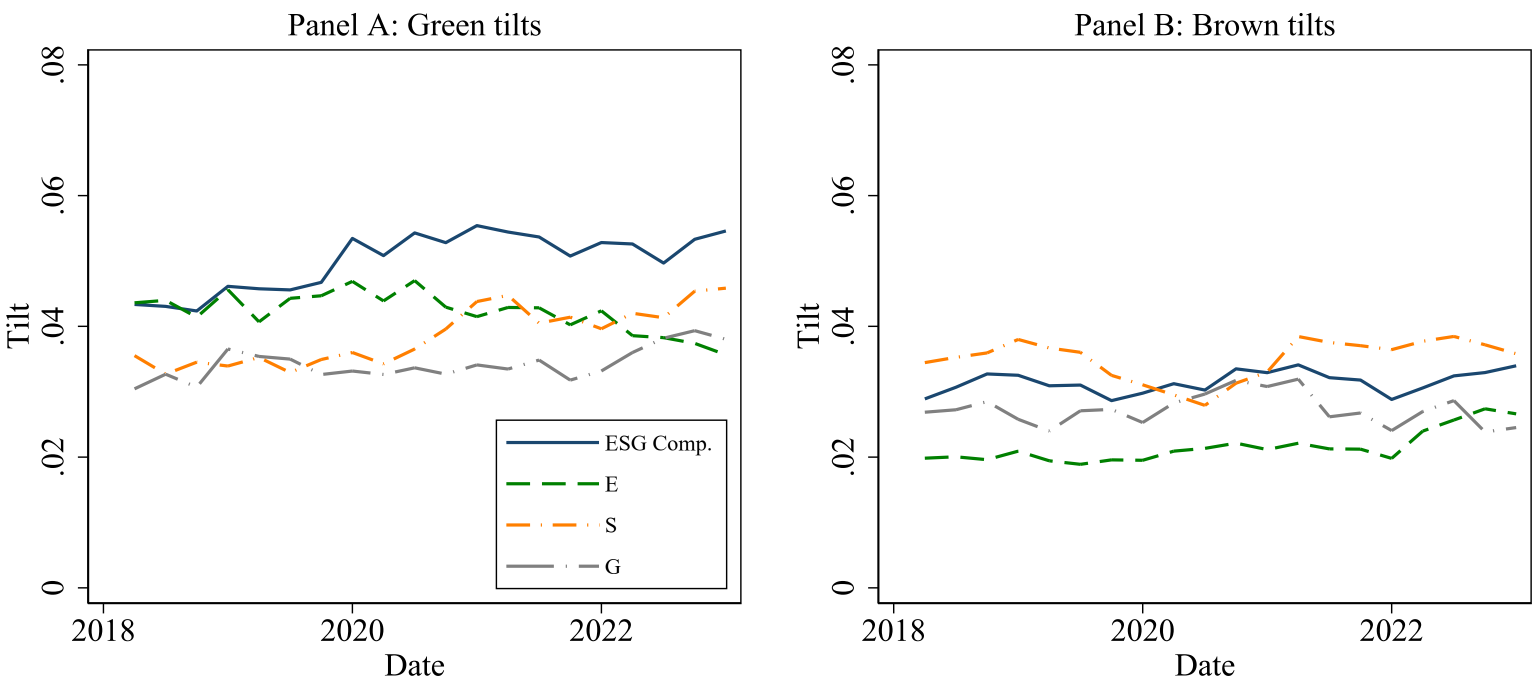


Figure B.14. Green and brown tilts (version with Sustainalytics scores). This figure plots the same quantities as Figure 3 but with Sustainalytics data.

Figure B.15. GMB tilts of 13F filers and non-filers (version with Sustainalytics scores). This figure plots the same quantities as Figure 4 but with Sustainalytics data.

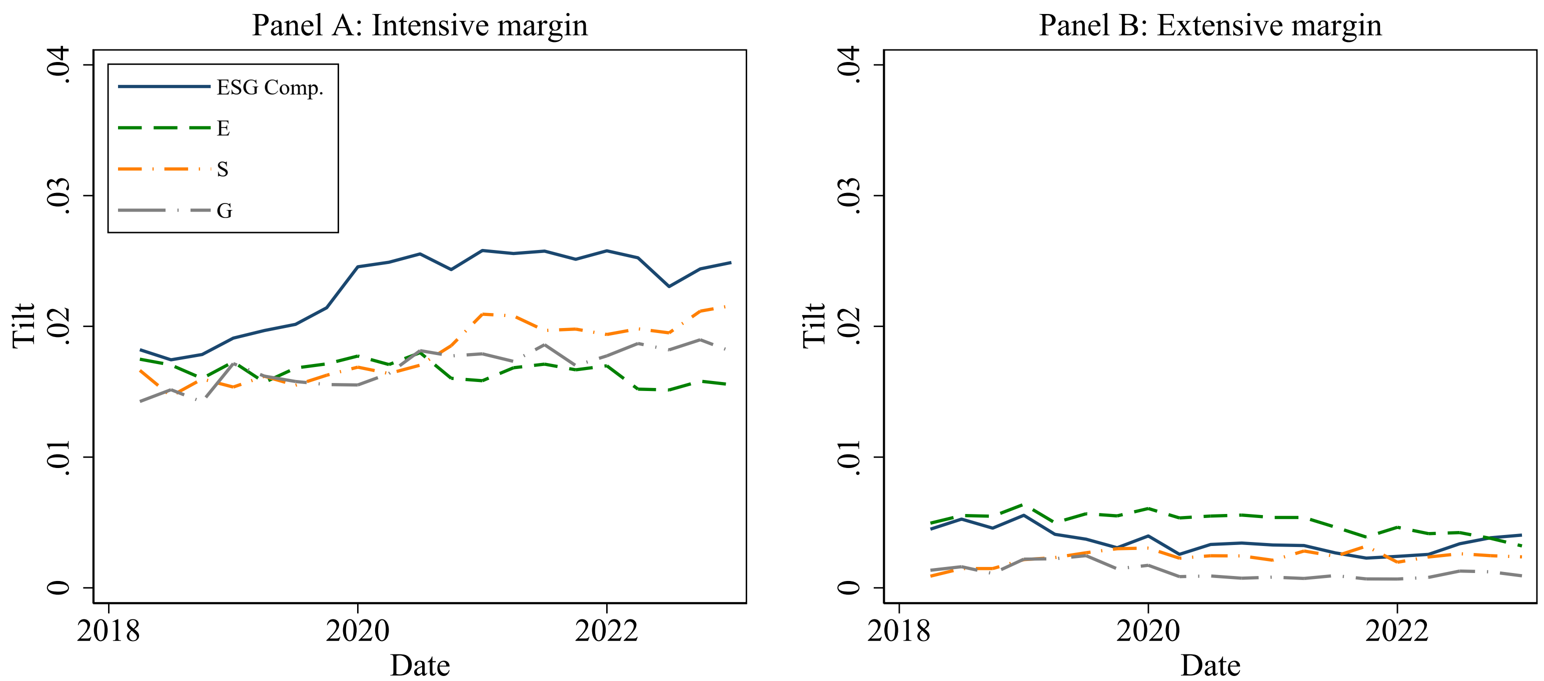


Figure B.16. Divestment from brown stocks (version with Sustainalytics scores). This figure plots the same quantities as Figure 5 but with Sustainalytics data.

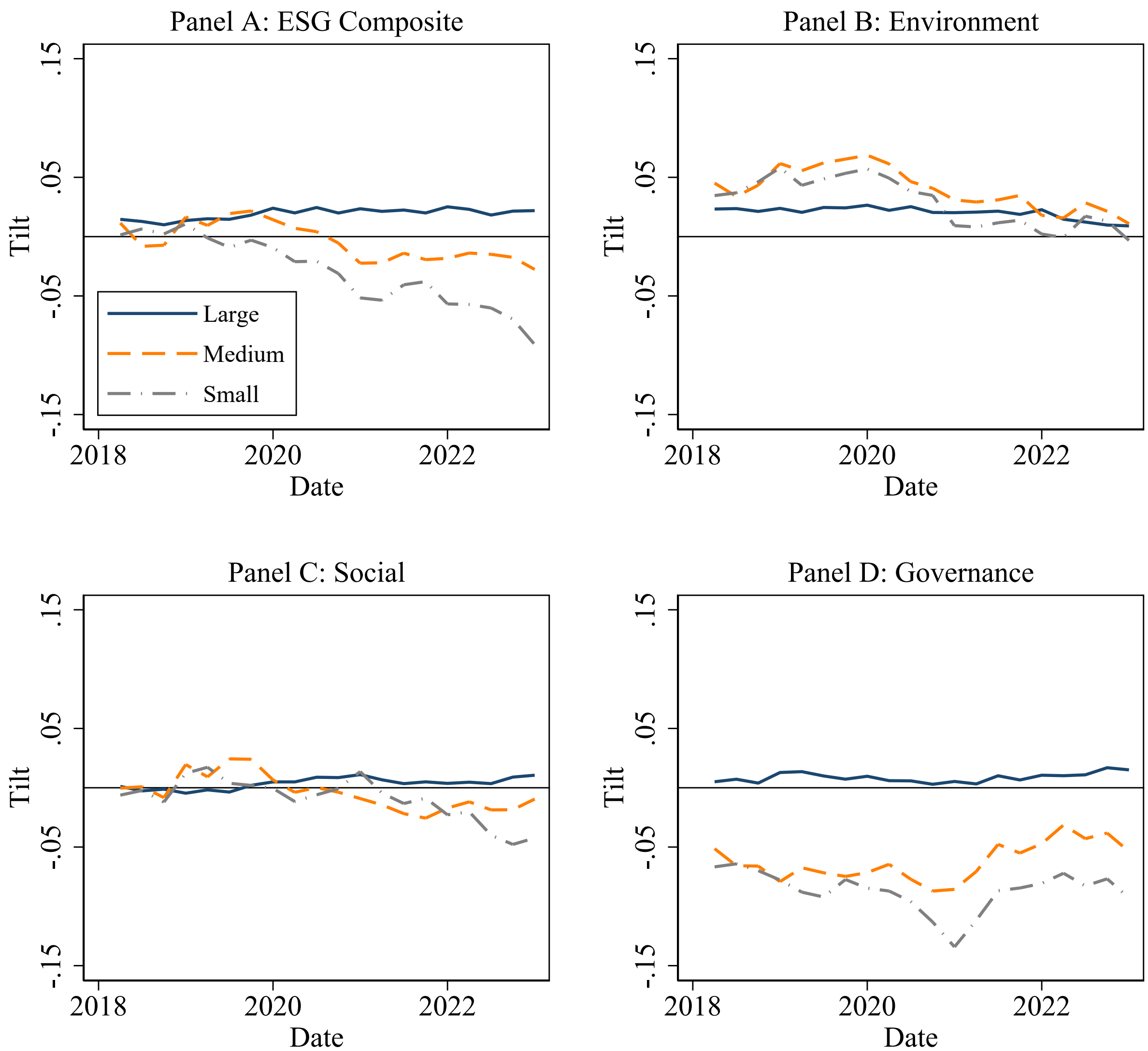


Figure B.17. Institution size and greenness (version with Sustainalytics scores). This figure plots the same quantities as Figure 6 but with Sustainalytics data.

Table B.11
Aggregate tilts
(version with Sustainalytics scores)

This table is the counterpart of Table 1 but with Sustainalytics data.

	Estimated Tilt			Standard Error		
Year	Total	Intensive	Extensive	Total	Intensive	Extensive
2019	0.061	0.057	0.018	0.002	0.002	0.001
2020	0.062	0.056	0.018	0.002	0.002	0.001
2021	0.066	0.061	0.018	0.002	0.002	0.001
2022	0.061	0.055	0.018	0.002	0.002	0.001
2023	0.063	0.058	0.015	0.002	0.002	0.001

Table B.12: Which institutions are greener?
(version with Sustainalytics scores)

This table shows the same quantities from Table 2 but with Sustainalytics data. All regressions use 50,309 institution×quarter non-missing observations from 2019q1–2023q4.

	No Fixed Effects				Time Fixed Effects				Institution Fixed Effects			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0212	0.0051	0.0104	0.0195	0.0210	0.0048	0.0103	0.0195	0.0012	-0.0068	-0.0018	0.0189
	(6.30)	(1.79)	(3.22)	(5.79)	(6.22)	(1.68)	(3.19)	(5.79)	(0.16)	(-0.85)	(-0.21)	(2.20)
log(AUM) × trend	0.1093	0.0440	0.0640	0.0239	0.1059	0.0391	0.0618	0.0275	0.0920	0.0477	0.0598	0.0180
	(5.81)	(2.58)	(3.38)	(1.22)	(5.63)	(2.28)	(3.25)	(1.39)	(5.09)	(2.88)	(3.14)	(0.94)
Trend	0.9779	0.2761	0.5804	0.3357					0.8182	0.3202	0.5306	0.2757
	(4.91)	(1.54)	(2.92)	(1.64)					(4.35)	(1.87)	(2.73)	(1.39)
Active share	0.0603	0.1055	0.0212	0.0053	0.0607	0.1064	0.0220	0.0045	-0.0056	0.0221	-0.0715	0.0713
	(2.34)	(4.35)	(0.85)	(0.19)	(2.36)	(4.38)	(0.88)	(0.16)	(-0.10)	(0.41)	(-1.26)	(1.27)
1(UNPRI)	0.0277	0.0378	0.0081	0.0064	0.0275	0.0375	0.0080	0.0068	0.0100	0.0120	0.0151	-0.0201
	(2.06)	(3.15)	(0.67)	(0.47)	(2.05)	(3.13)	(0.65)	(0.50)	(0.45)	(0.56)	(0.70)	(-0.97)
1(Inv. advisor)	0.0146	0.0269	-0.0187	0.0223	0.0146	0.0268	-0.0187	0.0224				
	(0.55)	(1.17)	(-0.72)	(0.72)	(0.55)	(1.17)	(-0.72)	(0.72)				
1(Bank)	-0.0195	0.0072	-0.0181	-0.0134	-0.0194	0.0073	-0.0181	-0.0134				
	(-0.68)	(0.29)	(-0.66)	(-0.40)	(-0.67)	(0.30)	(-0.66)	(-0.40)				
1(Pension/endowment)	0.0505	0.0391	0.0155	0.0328	0.0507	0.0392	0.0155	0.0332				
	(1.56)	(1.47)	(0.46)	(0.91)	(1.56)	(1.47)	(0.46)	(0.92)				
1(Europe)	0.0408	0.0375	0.0105	0.0270	0.0407	0.0373	0.0103	0.0271				
	(2.21)	(2.36)	(0.56)	(1.58)	(2.20)	(2.35)	(0.55)	(1.58)				
1(Rest of world)	0.0998	0.0674	0.0037	0.1242	0.0999	0.0675	0.0037	0.1244				
	(4.43)	(3.51)	(0.18)	(4.52)	(4.43)	(3.51)	(0.18)	(4.52)				
R^2	0.023	0.018	0.003	0.021	0.024	0.019	0.004	0.022	0.653	0.652	0.604	0.662
R^2 (FEs only)	N/A	N/A	N/A	N/A	0.003	0.004	0.001	0.001	0.651	0.650	0.604	0.662
p (Inst. types equal)	0.015	0.152	0.513	0.118	0.015	0.154	0.512	0.117	N/A	N/A	N/A	N/A

Table B.13: Green and brown tilts (version with Sustainalytics scores)

This table shows the same quantities from Table 3 but with Sustainalytics data.

	Green Tilts				Brown Tilts			
	ESG	Env.	Soc.	Gov.	ESG	Env.	Soc.	Gov.
log(AUM)	0.0085	0.0018	0.0035	0.0062	-0.0127	-0.0032	-0.0069	-0.0132
	(4.13)	(1.08)	(1.74)	(3.22)	(-6.35)	(-1.89)	(-3.66)	(-6.15)
log(AUM) $\times$ trend	0.0446	0.0232	0.0257	0.0104	-0.0646	-0.0209	-0.0383	-0.0134
	(3.75)	(1.96)	(2.22)	(0.93)	(-5.58)	(-2.13)	(-3.29)	(-0.98)
Trend	0.5106	0.1690	0.3179	0.2277	-0.4671	-0.1082	-0.2608	-0.1060
	(3.95)	(1.35)	(2.59)	(1.91)	(-3.86)	(-1.04)	(-2.13)	(-0.76)
Active share	0.1780	0.2253	0.1655	0.1604	0.1177	0.1192	0.1454	0.1560
	(11.45)	(15.49)	(10.68)	(9.97)	(7.71)	(8.38)	(10.11)	(9.16)
1(UNPRI)	0.0173	0.0263	0.0028	-0.0092	-0.0104	-0.0114	-0.0056	-0.0157
	(1.94)	(3.21)	(0.35)	(-1.12)	(-1.47)	(-1.84)	(-0.84)	(-2.02)
1(Inv. advisor)	-0.0003	0.0135	-0.0155	0.0111	-0.0149	-0.0134	0.0032	-0.0112
	(-0.02)	(1.08)	(-1.13)	(0.62)	(-0.87)	(-0.92)	(0.17)	(-0.60)
1(Bank)	-0.0198	-0.0023	-0.0172	-0.0021	-0.0003	-0.0095	0.0009	0.0113
	(-1.28)	(-0.16)	(-1.16)	(-0.11)	(-0.02)	(-0.62)	(0.05)	(0.54)
1(Pension/endowment)	0.0286	0.0163	0.0229	0.0210	-0.0218	-0.0228	0.0083	-0.0118
	(1.40)	(1.02)	(1.14)	(0.97)	(-1.16)	(-1.43)	(0.40)	(-0.55)
1(Europe)	0.0274	0.0311	0.0167	0.0170	-0.0133	-0.0063	0.0066	-0.0100
	(2.26)	(2.80)	(1.45)	(1.77)	(-1.41)	(-0.86)	(0.65)	(-0.95)
1(Rest of world)	0.0722	0.0486	0.0095	0.1005	-0.0277	-0.0186	0.0056	-0.0239
	(4.54)	(3.23)	(0.73)	(5.66)	(-2.72)	(-2.67)	(0.49)	(-1.72)
R^2	0.051	0.067	0.028	0.047	0.032	0.026	0.029	0.036
p (inst. types equal)	0.007	0.126	0.067	0.150	0.250	0.371	0.953	0.277

B.6. Additional results on mutual funds' tilts

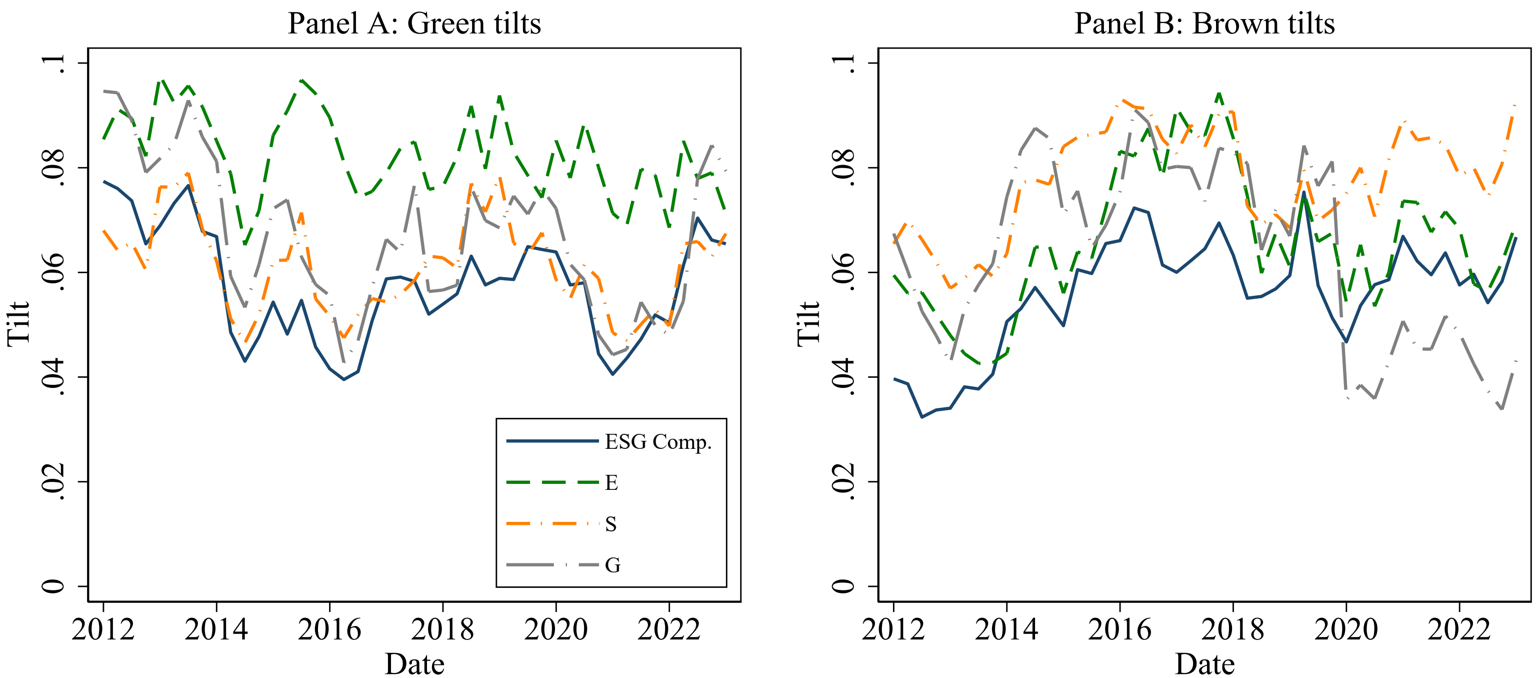


Figure B.18. Active mutual funds' green and brown tilts. This figure plots the same quantities as Figure 10 but with the active mutual fund sample.

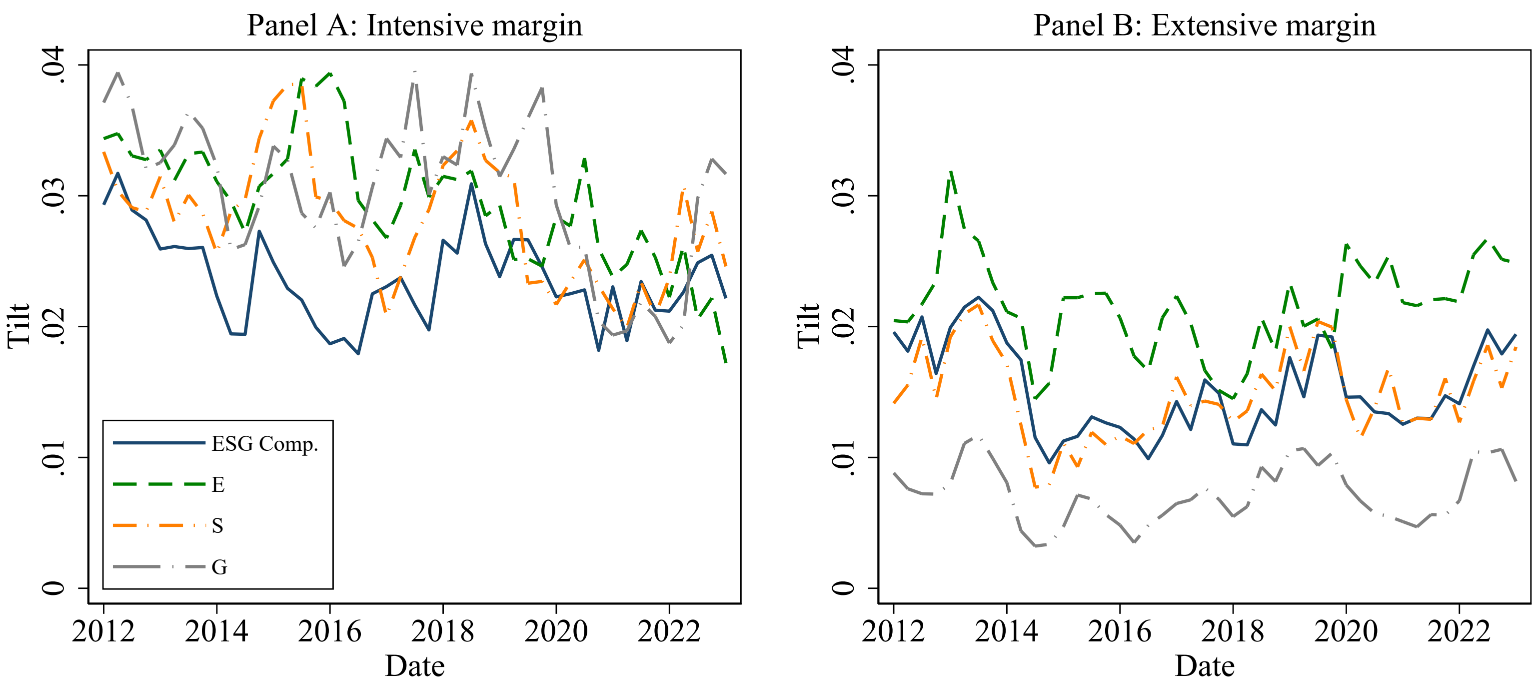


Figure B.19. Active mutual funds' divestment from brown stocks. This figure plots the same quantities as Figure 11 but with the active mutual fund sample.